frontiers in Remote Sensing

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Editorial: Machine learning for advanced remote sensing: from theory to applications and societal impact

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Editorial on the Research Topic
Machine learning for advanced remote sensing: from theory to applications and societal impact

Machine learning is reshaping remote sensing from a primarily observational science into an operational source of spatial intelligence for decision-making. Yet this transition requires more than improved benchmark accuracy. Remote-sensing models must be scalable across sensors and regions, reliable under imperfect observation conditions, computationally feasible for real-world deployment, and sufficiently interpretable to support policy, safety-critical, and public-good applications. This Research Topic was motivated by these requirements. It brings together studies that connect methodological advances in machine learning with spatially explicit applications in agriculture, infrastructure, maritime monitoring, satellite autonomy, image enhancement, and ecosystem assessment.

A central theme emerging from this Research Topic is that remote-sensing machine learning remains most powerful when it is coupled with domain knowledge and spatial-temporal reasoning. In "*Coffee extraction from remote sensing imagery based on multiple features: a case study of Pu'er City, China*", Huang et al. show that coffee mapping can be improved by integrating Sentinel-2 spectral information with vegetation indices, texture, terrain, administrative context, field samples, and phenological segmentation. The study illustrates that crop classification is not merely a pixel-level recognition task; it is a spatial-temporal inference problem shaped by crop calendars, topography, management geography, and regional ecological conditions.

A related insight is developed in "*Operationalizing remote sensing methods for smallholder dry season irrigation detection in sub-Saharan Africa*". Siddiqui et al. demonstrate that phenology-based irrigation detection is effective in semi-arid regions with a prolonged dry season, but less transferable to humid regions where non-irrigated vegetation does not senesce sufficiently. This contribution is important because it links classification validity to landscape process. It also shows how remote sensing can support food security, water planning, and energy infrastructure decisions by identifying where farmer-led dry-season cultivation is already occurring.

Operational remote sensing also depends on models that are both accurate and deployable. In "*HPLNet: a hierarchical perception lightweight network for road extraction*", Cui et al. address the challenge of extracting narrow, elongated, and often occluded roads from high-resolution satellite imagery. Their hierarchical perception design combines local detail preservation with broader semantic representation while reducing model complexity. This study highlights a broader requirement for infrastructure mapping: future models must preserve topological connectivity and fine spatial detail without becoming too computationally expensive for large-area or edge deployment.

Computational efficiency is also central to "*Efficient remote sensing image super-resolution with residual-enhanced wavelet and key-value adaptation*". Lu et al. propose a super-resolution architecture that combines residual-enhanced wavelet decomposition, linear attention, and quad-directional scanning. The work responds to limitations of CNNs, Transformers, and state-space models by improving spatial detail while reducing computational burden. Its relevance extends beyond image enhancement, because super-resolution can improve downstream applications in urban monitoring, precision agriculture, and environmental assessment without requiring costly sensor upgrades.

Reliability under degraded observation conditions is another major concern. In "*CARP: cloud-adaptive robust prompting of vision-language models for ship classification under cloud occlusion*", Zhan et al. introduce a cloud-aware prompting framework for fine-grained ship classification and provide a benchmark designed for cloud-occluded maritime imagery. Their work shows that large vision-language models cannot simply be transferred to remote sensing without adaptation. Atmospheric interference can corrupt visual features, weaken semantic alignment, and reduce data utility, particularly in few-shot settings. This study therefore points toward physically aware and degradation-aware foundation models for Earth observation.

The Research Topic also expands the meaning of operational reliability to include data security and trusted deployment. In "*A privacy-preserving, on-board satellite image classification technique incorporating homomorphic encryption and transfer learning*", Roy et al. integrate homomorphic encryption with transfer learning for satellite image classification. Their framework addresses the need for secure, low-latency, and memory-conscious on-board inference. As Earth observation systems become more autonomous and as remotely sensed data are used in sensitive contexts, privacy preservation, authorization, and communication constraints will become central design considerations alongside accuracy.

Finally, "*3D colored point cloud classification of a deep-sea cold-water coral and sponge habitat using geometric features and machine learning algorithms*" by Morsy et al. extends this Research Topic beyond conventional 2D satellite imagery. Using structure-from-motion point clouds derived from remotely operated vehicle surveys, the authors classify deep-sea benthic habitats by combining RGB and geometric features. This study demonstrates the value of 3D spatial structure for ecological remote sensing and highlights the role of machine learning in monitoring vulnerable marine habitats. It also reveals continuing challenges in underwater sensing, including illumination variability, color distortion, limited labels, and the cost of expert annotation.

Together, these contributions suggest several priorities for future research. First, remote-sensing foundation models should become more geographically and physically aware, incorporating sensor characteristics, atmospheric effects, seasonal dynamics, and spatial context. Second, model complexity should be matched carefully to data availability and heterogeneity in order to reduce both overfitting and underfitting. Transferability should be evaluated systematically across regions, sensors, seasons, and ecological regimes, rather than inferred from within-site or randomly partitioned test accuracy. Third, validation strategies should explicitly account for spatial and temporal autocorrelation through geographically separated test sets, spatially or temporally blocked cross-validation, and independent external reference data. Uncertainty quantification, probability calibration, explainability, and spatial statistical validation should also be integrated into operational workflows, especially where outputs inform policy or safety-critical decisions. Fourth, efficiency, privacy, and edge deployment should be treated as core scientific requirements, not merely engineering constraints. Fifth, benchmark datasets should better represent real-world degradation, including cloud cover, occlusion, fragmented fields, rare classes, and underrepresented environments. Finally, the societal value of remote-sensing machine learning should be assessed more explicitly by asking how model outputs improve resilience, sustainability, equity, conservation, or resource allocation.

An additional challenge for operational remote-sensing machine learning is the risk of model overfitting or underfitting and the need for rigorous validation. This Research Topic is particularly important because remotely sensed observations are spatially and temporally autocorrelated, meaning that randomly divided training and test samples may contain highly similar neighbouring observations and consequently produce overly optimistic accuracy estimates. Overfitting may also arise when highly complex models are trained on geographically limited, imbalanced, or sparsely labelled datasets, whereas underfitting can prevent models from capturing the spectral, spatial, and temporal heterogeneity of real-world landscapes. Reliable evaluation should therefore go beyond conventional random train–test splits and include spatially or temporally blocked cross-validation, geographically independent test regions, cross-sensor and cross-season assessments, and, where possible, external validation using field observations or independently collected reference data. Reporting uncertainty, calibration, class-specific performance, and variability across validation folds is equally important for determining whether model outputs are sufficiently robust for operational and societal applications.

This Research Topic shows that the future of machine learning in remote sensing lies in the integration of methodological innovation with spatial reasoning and societal purpose. The studies collected here advance phenology-aware crop and irrigation mapping, lightweight infrastructure extraction, efficient image enhancement, cloud-robust vision-language modelling, privacy-preserving satellite intelligence, and 3D ecological classification. Collectively, they move the field beyond algorithmic novelty toward trustworthy, scalable, and actionable remote-sensing systems for public good.

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