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Review Article

Structured Comparative Review of Remote Sensing, Hyperspectral Imaging, and Deep Learning for Agricultural Monitoring and Crop Classification

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Abstract

Climate-resilient agriculture increasingly relies on remote sensing, hyperspectral imaging (HSI), machine learning, and deep learning to support crop classification, disease and stress detection, yield-related assessment, and field monitoring. This structured comparative review synthesizes 50 core empirical studies drawn from an 80-reference evidence base and examines their sensing platforms, learning strategies, reported performance measures, deployment constraints, and reproducibility characteristics. The evidence is organized by multispectral and time-series sensing, HSI and band selection, unmanned aerial vehicle (UAV) and high-resolution monitoring, crop and land-cover classification, disease and weed detection, yield and soil assessment, and Internet of Things (IoT)/cloud-enabled monitoring. Numerical results are reported only when explicitly stated in the source study; unreported metrics are marked as not reported, and no metric is inferred from a related method or dataset. Because datasets, sensors, crops, class definitions, geographic regions, and validation protocols differ substantially, performance values are interpreted within their original experimental context rather than used to rank methods across studies. The synthesis identifies recurring limitations involving annotation scarcity, spectral-domain shift, class imbalance, external validation, computational cost, and incomplete reproducibility reporting, and it outlines research priorities for transferable, interpretable, and operational agricultural intelligence.

Keywords: *Crop Classification; Deep Learning; Hyperspectral Imaging; Precision Agriculture; Remote Sensing; Structured Comparative Review*

Introduction

Population growth, fast urbanization, climatic unpredictability, soil nutrient depletion, and environmental concerns are changing agriculture worldwide scenarios. Low statistical reporting, manual scouting, and sporadic field sampling no longer ensure crop resilience. AI, hyperspectral imaging, and remote sensing (Jamil *et al*., 2025; Chandra & Nidamanuri, 2025; Cherid *et al*., 2025) are important for continuous, fine-grained insights into vegetation physiology, growth patterns, and environmental interactions.

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Need and Relevance

Converging factors require advanced agricultural surveillance. Early disease progression, nutritional stress, and canopy modifications before yield loss are difficult to detect using farmer-driven monitoring. Heat waves, water shortages, and cyclones necessitate quick damage assessment and response. Hyperspectral imaging finds metabolic indicators before visual signs with hundreds of contiguous spectral bands. Sentinel, Landsat, and Earth Observing-1 (EO-1) provide continuous temporal coverage, while UAVs provide centimeter-level spatial detail for plot-scale analytics. Machine learning turns rich signals into intelligence, and deep learning architectures reveal complex non-linear relationships humans cannot understand.

Motivation for this Review

Despite advances in imaging, computer algorithms, and sensor integration, the scientific environment remains fragmented. Reviews frequently focus on high-level conceptual presentations, cover a few strategies, or lack metric-driven comparisons that practitioners require to pick between approaches. Additionally, environmental, acquisition, and crop physiology heterogeneity reduces the transferability of isolated findings. Agronomists, policymakers, government agencies, and crop insurers are confused by this fragmentation. Another reason exists without clear evaluation frameworks. Studies use various metrics (accuracy, precision, recall, F1-score, R^2 values, root mean square error (RMSE), and spectral dimensionality reduction percentages), making cross-study comparisons difficult. No uniform performance tabulation hampers operating precision agricultural pipelines. A structured, source-traceable synthesis can bridge methodological gaps while preserving differences among datasets and validation protocols (Zhang *et al*., 2023).

Scope and Breadth of the Review

This work brings together fifty recent studies on multisensor fusion, spectral-spatial filtering, metaheuristic band selection, transformer-based spectral encoding, normalized difference vegetation index (NDVI)-based phenological mapping, cloud-integrated random forests, generative augmentation for class imbalance, thermal anomaly detection, multivariate proximal red-green-blue (RGB) analytics, and IoT-enabled soil Cotton, rice, potatoes, wheat genotypes, mangrove vegetation, floriculture, heat-stress detection (Kumar *et al*., 2024; Arulananth *et al*., 2024), land-use evolution, ecological disturbance, urban heat island influence, and pest-disease recognition are classified. The paper compares hybrid convolutional neural network (CNN)-transformer models to support vector machine (SVM) kernels, penalty-based reasoning systems, and domain-transfer frameworks using numerical measures in tables. Based on accuracy distributions, F1-score patterns, dimensionality reduction efficiency, and correlation values, deep spectral-spatial hybridization beats feature-engineered pipelines in classification fidelity (Zhang *et al.* 2026).

Contribution and Novelty

Contribution relative to recent reviews. Recent surveys have examined narrower parts of the same research landscape: Tejasree and Agilandeeswari (2024) focus on hyperspectral image classification and prediction techniques. Hossen *et al*. (2025) concentrate on transfer learning in agriculture; Khan *et al*. (2025) review automated plant-disease detection; Song *et al*. (2025) synthesize deep learning for hyperspectral image classification; and Radočaj *et al*. (2026) examine satellite remote sensing for crop-yield prediction. The present review complements these works by jointly organizing evidence across multispectral and hyperspectral sensing, UAV and satellite platforms, crop classification, disease and stress analysis, yield/soil assessment, and IoT/cloud-supported monitoring. Its principal contribution is therefore not a claim of unique metric synthesis, but a cross-domain, source-traceable comparison that couples reported performance with evidence-quality attributes such as dataset context, validation design, geographic coverage, reproducibility, and deployment constraints (Li *et al*., 2025).

Impact on Precision Agriculture Research

The analytical conclusions of this research will help system designers, policymakers, and computational agronomists choose sensors, computational infrastructure, and data annotation methods. Transformer approaches outperform pure convolutional pipelines, although their processing overhead favours cloud inference over edge deployment. IoT-driven soil evaluation frameworks may operate effectively in real time but need sensor drift calibrations. In agricultural economies with expensive field annotation and few agronomists, few-shot, transfer-learning-driven disease diagnosis is strategic. Farmers with few labelled samples may predict uncommon pest outbreaks with meta-

learning. Generative adversarial augmentation reduces minority crop variety class imbalance, making automated decision models fair.

Closing Perspective

As climate change and sustainability affect agriculture, these technologies provide the computational framework for a paradigm shift. Hyperspectral imaging, remote sensing, deep learning, and cloud compute support increasingly predictive agricultural monitoring. Structured comparative analysis provides clarity, a benchmarking framework, and foresight to accelerate the transformation and enable precision-aware, environmentally resilient farming systems.

Review Methodology

A structured literature search was defined around agricultural remote sensing and intelligent crop monitoring. The search protocol covered Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, using combinations of the terms “remote sensing,” “hyperspectral imaging,” “multispectral,” “UAV,” “satellite,” “crop classification,” “plant disease,” “crop stress,” “yield prediction,” “soil monitoring,” “machine learning,” “deep learning,” “CNN,” and “transformer.” The core evidence synthesis prioritized English-language, peer-reviewed empirical studies published during 2023-2025 that evaluated an agricultural monitoring, classification, prediction, segmentation, or diagnosis task using remotely sensed or proximal imaging data and reported sufficient methodological or outcome information for structured extraction. Review articles, older seminal studies, bibliometric papers, and adjacent application studies were retained only when they supplied methodological context or helped interpret the evidence base; they were not treated as core comparative studies. Duplicate records, non-agricultural studies, papers without a relevant sensing/learning component, and papers without extractable empirical evidence were excluded from the core synthesis. For each eligible study, the extraction form recorded sensing modality, crop/task, dataset characteristics, geographic setting, class structure, learning method, validation design, reported metrics, limitations, and reproducibility indicators.

Study-count clarification. The manuscript contains 80 references in total, but only 50 studies form the core structured comparative synthesis presented in the main evidence tables. The remaining 30 references are used for methodological background, recent review-to-review comparison, historical context, or adjacent applications and are not pooled with the 50 core studies. This distinction is maintained throughout the revised manuscript so that the number of studies in the evidence synthesis is not confused with the total number of references.

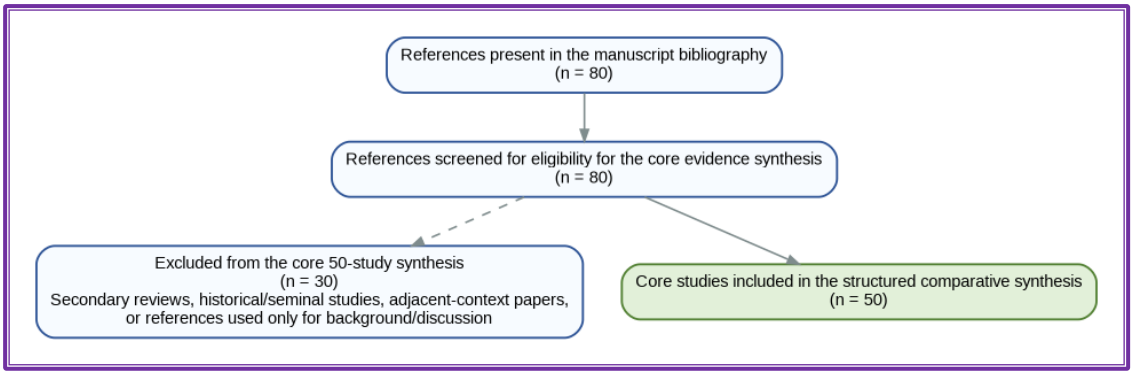


Figure 1: *Taxonomy of Paper Selection*

Figure 1 Retrospective evidence-accounting flow used to distinguish the 50 core studies from the 30 contextual references in the final bibliography. Because the original database-level hit counts were not retained, the figure reports verifiable evidence-accounting counts rather than reconstructing unsupported identification-stage numbers.

Thematic Review of Existing Methods

The literature is organized by sensing modality and agricultural task so that extracted study findings are presented before interpretation. Within each theme, the discussion first summarizes the data source, model class, and reported outcome, and then examines limitations, transferability, and

practical implications. This structure reduces repetition and avoids treating heterogeneous applications as a single performance benchmark.

Multispectral and Multi-temporal Remote Sensing

Multispectral and time-series studies emphasize phenological separability, revisit frequency, and cloud-robust temporal reconstruction, with Sentinel and Landsat observations frequently used for crop-area and seasonal mapping.

Hyperspectral imaging (HSI) analysis is used to classify crops because it can detect tiny spectral variations over hundreds of continuous bands. These fine-grained spectral fingerprints distinguish botanical species, development stages, and stress situations beyond multispectral methods' resolution. The research gradually shifts from conventional feature extraction to statistical, empirical, and learning-driven frameworks. Combining satellite sources with machine learning ensembles enhanced early-stage crop mapping discriminating accuracy using Sentinel-2A and Landsat 8–9 data (Jamil *et al*., 2025). Besides spectrum richness, such studies iteratively optimize input statistics and model behavior. HSI researchers struggle to balance redundancy with high spectral complexity. Multiple articles recommend optimization and empirical correlation-based band selection to reduce noise and correlation. New frameworks remove redundant channels while maintaining critical spectral responses for categorization, reducing computer overhead (Kumar *et al*., 2024). In hybrid feature selection algorithms like moth-flame optimization in CNN pipelines, deep architectures and metaheuristic search improve spectral subset performance and compactness. Plant-level drone photography refines and contextualizes band subsets for categorization using nature-inspired optimization (Sarma & Nidamanuri, 2025). Knowledge transfer across multiple geographies is improved by object-based spectral libraries trained on drone-borne hyperspectral acquisitions of farmlands (Chandra & Nidamanuri, 2025). New frameworks like HyperFast can accelerate inference while controlling field-scale heterogeneity with spectral and spatial guiding filters (Cherid *et al*., 2025; Thatha *et al.,* 2024). For precise crop type discrimination, deep convolutional-transformer hybrid networks can capture local patch patterns and global spectral correlation (Guo *et al*., 2025). These innovations tackle the persistent spectral-spatial feature synergy issues.

Table 1: *Model's Empirical Review Analysis*

Reference	Method Used	Findings	Strengths	Limitations	Recommendations to Overcome Limitations
Jamil *et al*., 2025	Fusion-based machine learning using Sentinel-2A and Landsat8–9	Demonstrated improved early-stage crop discrimination through multisensor spectral fusion	Enhances spectral richness; boosts early phenological separability	Dependent on temporal availability of satellite passes	Integrate gap-filling interpolation and cloud-robust temporal models
Chandra & Nidamanuri, 2025	Object-based spectral library transfer on drone HSI	Enabled robust knowledge transfer for crop detection across varied farms	Reduces labeling effort; supports scalable reuse	Sensitive to illumination variability	Apply advanced normalization and adaptive spectral calibration
Cherid *et al*., 2025	Spectral-spatial guided filtering (HyperFast)	Increased classification efficiency while retaining spatial context in UAV HSI	Fast inference; preserves edge boundaries	Performance declines in highly heterogeneous canopies	Integrate multiscale spatial attention mechanisms
Kumar *et al*., 2024	Band selection framework with statistical optimization	Reduced spectral redundancy while retaining discriminative bands	Lowers computational complexity; avoids overfitting	Selection stability varies by crop type	Combine band-prior knowledge with stability-regularized selection
Arulananth	AI-assisted	Highlighted	Detects thermal	Limited	Incorporate crop-

et al., 2024	hyperspectral heat pattern analysis	heat-driven stress relevant to global warming impacts on crops	anomalies early	agricultural specificity	specific evapotranspiration spectral markers
Kaushik *et al*., 2025	Machine learning discrimination of organically vs. conventionally grown vegetables	Differentiated cultivation practices using hyperspectral signatures	Sensitive to subtle biochemical shifts	Limited generalization across soil types	Expand spectral libraries with regional calibration sets
Taheri *et al*., 2024	Ensemble deep learning for rice seed variety classification	Achieved high precision among morphologically similar seeds	Excellent fine-granularity discrimination	Requires expensive spectral acquisition setups	Promote low-cost sensor adaptation and transfer learning
Sarma & Nidamanuri, 2025	Metaheuristic band selection on drone HSI	Improved plant-level classification accuracy via nature-inspired optimization	Efficient convergence; domain-adaptive	Sensitive to parameter tuning	Auto-tune parameters using meta-learning frameworks
Xue *et al*., 2024	Model transfer-based crop classification	Allowed portability of learned models across river basin regions	Reduces training cost and data dependency	Drop in accuracy when spectral domain shifts	Integrate spectral alignment and domain adversarial learning
Kaur *et al*., 2024	Score-level fusion hybrid model for cotton classification	Combined multiple features for improved cotton mapping	Fusion boosts robustness	Fusion rules may be dataset-dependent	Apply adaptive fusion weights learned by neural meta-models
Rather & Alotaibi, 2025	ML + hyperspectral analysis for potato growth/yield	Enabled cultivar identification and yield estimation trends	Assists breeding and crop planning	Accuracy sensitive to canopy maturity	Incorporate multi-temporal progression curves
Guo *et al*., 2025	Hybrid CNN-Transformer (CMTNet) for UAV-HSI	Leveraged spectral + global attention for precise classification	Captures non-local patterns	High computational load	Use hierarchical token reduction and quantization
Tejasree & Agilandeeswari, 2024	Extensive review of HSI techniques	Documented challenges such as noise, redundancy, and domain shifts	Comprehensive diagnostic perspective	Lacks experimentally validated solutions	Translate review insights into benchmark challenge datasets
Zheng *et al*., 2025	Hyperspectral + high-spatial resolution for complex vegetation	Enabled fine separability under dense cover conditions	Excellent canopy penetration capability	Spectral mixing in multi-layer canopies persists	Add sub-pixel unmixing with vegetation priors
Selvaraj & Saravanan, 2025	EO-1 hyperspectral mapping of degraded mangroves	Enhanced mapping accuracy in degraded zones	Shows spectral resilience in stressed vegetation	Limited transferability beyond coastal forests	Develop biome-conditioned transfer functions
Arain *et al*., 2025	Deep learning for land	Provided high accuracy across varied	Strong generalization	Requires large labelled datasets	Implement self-supervised agricultural pretext tasks

	cover/use classification	environments			
Mohan *et al*., 2024	ML-driven ecosystem monitoring and disaster damage detection	Identified urban agricultural stress patterns post-disaster	Timely response assessment	Coarse classification granularity	Integrate hyperspectral anomaly detection kernels
Li *et al*., 2025	Neural network geochemical inversion with HSI	Predicted soil nutrients relevant to crop vigor	Supports precision fertilization strategies	Requires soil sampling ground-truth	Couple with adaptive soil sensor networks
Wang *et al*., 2024	Semantic segmentation of mangrove species via UAV RS	Distinguished species via spectral-spatial cues	Handles complex natural canopies	Constrained to forest environments	Cross-train models with agro-ecosystem datasets
Kumar, 2025	Deep learning for post-cyclone crop damage assessment	Enabled rapid classification of stressed crop zones	Fast emergency relevancy	May misclassify subtle physiological damage	Integrate hyperspectral moisture and pigment indices
Hossen *et al*., 2025	Review on agricultural transfer learning	Described beneficial reuse of pretrained models in agriculture	Reduces training resource demand	Domain shift remains a challenge	Employ style-transfer and feature alignment layers
Mahmood *et al*., 2025	Spatial assessment-driven backward feature reduction (RF)	Identified relevant features improving crop type accuracy	Interpretable feature ranking	Limited scalability to hyperspectral dimensionality	Extend to spectral group-aware reduction
Kumar *et al*., 2024	Survey of seed classification ML vs. DL	Compared multiple feature extraction strategies	Valuable methodological overview	Lacks hyperspectral specificity	Add spectral-texture hybrid descriptors
Kar *et al*., 2026	Multi-temporal Sentinel + ML for floriculture detection	Differentiated ornamental crop types using temporal spectral variation	Captures phenophase cues	Sentinel resolution sometimes coarse	Integrate UAV-level detail for refinement

Hyperspectral Imaging and Band Selection

HSI-based studies exploit contiguous spectral information to distinguish subtle biochemical and structural differences, while band-selection methods reduce redundancy and computational burden without assuming that reduced dimensionality guarantees cross-domain generalization.

Table 1 shows that HSI-based and multisensor approaches address different aspects of agricultural monitoring, ranging from band selection and spectral transfer to disease detection and temporal crop mapping. The evidence also shows that performance is sensitive to acquisition conditions, crop type, and validation design; therefore, the subsequent discussion focuses on these contextual factors rather than on isolated metric values.

Table 1 further indicates that machine learning can distinguish cultivation methods beyond classifications. Hyperspectral signals can identify organic and conventional vegetable production with advanced statistical techniques (Kaushik *et al*., 2025). Collective deep networks enable fine-grained seed variety categorization, advancing plant breeding spectral pattern recognition (Taheri *et al*., 2024). Hyperspectral analytics' versatility is shown by micro-scale studies with substantial empirical validation. Model transfer and domain adaptation are prevalent. Transfer learning pipelines that respond to environmental shifts' spectral variability improved crop classification in climatically dynamic river basins (Xue *et al*., 2024). Further studies reveal that pretrained spectrum representations

generalize across agricultural imaging tasks, but domain-specific calibration is essential (Hossen *et al*., 2025). Hyperspectral remote sensing has increasingly become the backbone of precision agriculture, as its rich, contiguous spectral bands allow subtle biochemical and structural differences between crops to be captured that broadband multispectral sensors simply cannot resolve (Song *et al*., 2025; Nikzadfar *et al*., 2024). While these capabilities are transformative in principle, hyperspectral data are also high-dimensional, noisy, and often scarce in labelled samples, which restricts their practical deployment across diverse agroecological zones (Guerri *et al*., 2024; Shuai *et al*., 2024). This results in longer development cycles for reliable classification pipelines, added computational overhead, and a persistent gap between research prototypes and field-ready systems. For this reason, deep learning architectures, ranging from hybrid CNN-transformer designs to Kolmogorov-Arnold inspired networks, have emerged as the tool of choice for automating hyperspectral crop analysis, since they are able to jointly exploit spatial and spectral cues at scale (Zhang *et al*., 2025; Zidi *et al*., 2025).

Systematic reviews of this literature converge on a common narrative: the field has moved from simple band-ratio indices toward end-to-end learned representations, but interpretability, dataset scarcity, and cross-sensor transferability remain open challenges (Bourriz*et al*., 2025; García-Vera *et al*., 2024; Barbedo, 2023). Early architectural work such as the IRX-1D network demonstrated that carefully engineered lightweight models could rival deeper, more resource-intensive designs on benchmark hyperspectral datasets, particularly when training samples were limited (Pal & Teja, 2020). Broader surveys of machine learning in agriculture reinforce this pattern, noting that crop management, and particularly disease detection and species discrimination, still accounts for the largest share of published applications (Liakos *et al*., 2018; Benos *et al*., 2021; Pokhariyal *et al*., 2023).

Beyond classification, remote sensing and machine learning are increasingly coupled to agronomic and crop-growth models to improve the accuracy of yield forecasting under variable field conditions (Ko *et al*., 2024). Deep transfer learning approaches have proven especially useful where labelled yield data are limited, allowing models trained on data-rich regions to be adapted to new crops and geographies with comparatively little additional supervision (Huber *et al*., 2024). Systematic literature reviews of this sub-domain confirm that the combination of dense satellite time series with deep learning consistently outperforms classical regression-based yield estimators, though performance still varies considerably by crop type and sensor resolution (Muruganantham *et al*., 2022; Farmonov *et al*., 2024). A recent bibliometric review of more than a thousand indexed studies further shows that this research area has grown rapidly since 2015, with multispectral missions such as Sentinel-2 and Landsat dominating the literature while hyperspectral and radar-based approaches represent an accelerating, if still comparatively small, share of the field (Radočaj *et al*., 2026; Sangeetha & Agilandeeswari 2025).

UAV and High-Resolution Monitoring

UAV and high-resolution platforms provide fine spatial detail for plant- and parcel-level analysis, but their reported gains depend strongly on flight conditions, illumination, calibration, and geographic transferability.

At the crop-type and land-cover mapping level, fusion-based decision strategies and attention-driven convolutional networks have been used to resolve spectrally similar classes that conventional pixel-based classifiers struggle to separate (Papadopoulos *et al*., 2024). Hybrid CNN-random forest frameworks and dual-attention architectures have shown particular promise for early-season crop mapping, where the number of available observations is naturally constrained by the growth stage of the crop (Kwak *et al*., 2021; Seydi *et al*., 2022). Reconstructed time-series inputs, generated to fill gaps caused by cloud cover or sensor revisit limitations, have likewise been shown to materially improve the robustness of deep learning-based crop maps relative to models trained on raw, incomplete imagery (Feng *et al*., 2023). Complementary work in fruit and citrus crop health assessment illustrates that convolutional feature extraction from hyperspectral imagery can support fine-grained disease classification even at the individual fruit or leaf level (Yadav *et al*., 2024).

Disease and stress detection remains one of the most active and practically consequential branches of this literature, since early identification directly limits yield loss and reduces reliance on reactive, resource-intensive interventions. Attention-driven segmentation approaches have been applied to cassava leaf imagery to separate diseased tissue from healthy canopy with greater precision than conventional thresholding methods (Sirisha *et al*., 2025), while comparable attention-based architectures have been developed for grape leaf disease identification under variable field lighting

and background clutter (Praveen *et al*., 2025). A related line of work has since scaled these ideas into lightweight, multi-crop detection models intended for deployment on resource-constrained edge devices, extending disease-screening capability beyond single-crop pipelines (Praveen *et al*., 2025). Taken together with adjacent contributions on confidentiality-preserving AI frameworks for agricultural cyber-physical monitoring networks and transformer-based classification of disaster-related field reports (Praveen *et al*., 2025; Sirisha *et al*., 2025), this body of work illustrates how the same deep learning toolkit that underpins hyperspectral crop classification is increasingly being repurposed for the wider ecosystem of agricultural monitoring, from canopy-level disease screening to farm-level disaster response.

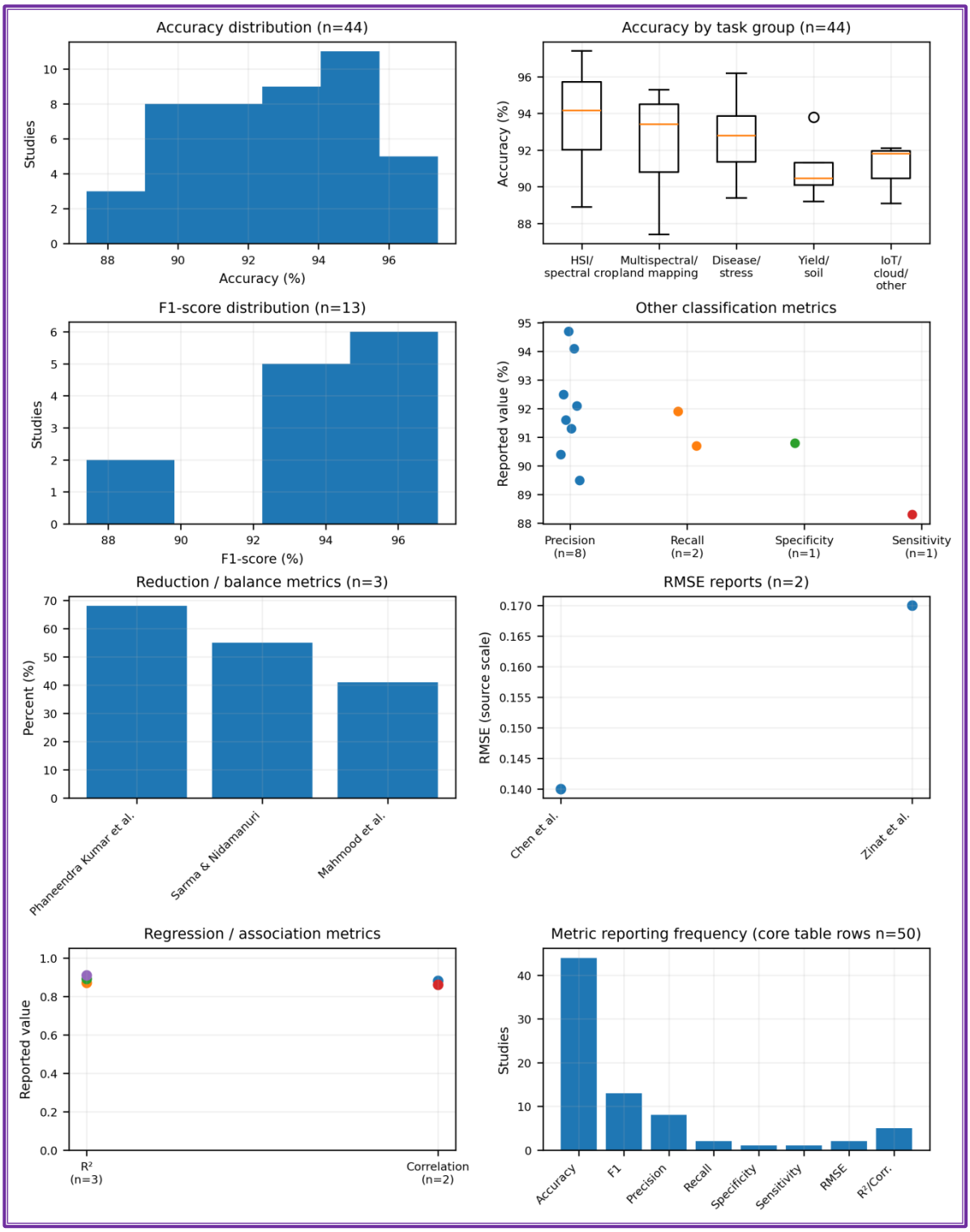


Figure 2: *Integrated Model Performance Analysis*

Figure 2 Descriptive evidence profile of the core review studies. Each panel is generated only from reported values for the metric shown; missing metrics are omitted rather than imputed. Panel-specific sample sizes (n) are stated in the titles. The plots summarize accuracy, F1-score, precision, recall/sensitivity/specificity, reduction metrics, RMSE, regression/association measures, and reporting frequency. They are descriptive and are not used to rank models trained on different datasets.

Crop and Land-Cover Classification

Crop-classification studies range from classical machine learning to CNN-transformer hybrids; their reported performance is interpreted together with class structure, sensor modality, and validation design rather than by raw accuracy alone.

Even random forest classifiers benefit from geographical assessment-based feature selection, proving statistical refinement makes classical machine learning useful (Mahmood *et al*., 2025). Deep learning has been utilized in disaster-driven agricultural damage assessment (Kumar, 2025), remote-sensing ecosystem monitoring (Mohan *et al*., 2024), and smart-weather crop recommendations. The drive toward real-time agricultural intelligence classifies land cover at large scale using hyperspectral imaging, cloud computing, and parcel-based image processing (Arain *et al*., 2025; Altun & Turker, 2025; El-Shirbeny *et al*., 2025). Hierarchical transformer topologies increase weed and pest dynamics localization in complex field conditions (Islam *et al*., 2025). Based on bibliometric analyses, spectral textural signals and deep feature hierarchies are driving agricultural disease detection research.

Table 2: *Model's Empirical Review Analysis*

Reference	Method Used	Findings	Strengths	Limitations	Recommendations to Overcome Limitations
Mohamed *et al*., 2025	Hybrid deep learning + rule-based forecasting using satellite imagery	Enhanced crop recommendation accuracy through environmental condition modeling	Integrates climatic intelligence	Rule-based components may underperform under novel weather extremes	Incorporate adaptive meteorological learning modules
Li *et al*., 2025	Spatio-temporal land use evolution analysis	Identified drivers affecting agricultural land transformation influencing classification patterns	Long-term historical insight	Limited spectral detail for canopy-level crop discrimination	Fuse hyperspectral time-series to refine crop-specific trends
Banerjee *et al*., 2025	Low-cost proximal RGB imaging + multivariate analysis	Successfully differentiated crop types at field scale using budget sensors	Affordable deployment	Lacks fine spectral continuity	Augment with simplified hyperspectral add-on modules
Jeba *et al*., 2024	NDVI time-series with dynamic crop calendar mapping	Improved tracking of spatiotemporal cropping patterns in heterogeneous regions	Effective phenological profiling	Limited sensitivity to subtle pigment shifts	Add narrowband reflectance features via HSI fusion
Meng *et al*., 2025	Dual recognition deep learning strategy	Accurately classified Camellia oleifera classes at high resolution	Robust multi-path inference	High model complexity	Implement model compression and architecture distillation
Islam *et al*., 2024	Sentinel-2 + in-situ spectroradiometer validation	Enhanced mapping precision for wheat under	Strong ground-truth correlation	Field sampling effort intensive	Employ UAV-based proxy sensing for rapid data collection

		heterogeneous conditions			
Singh & Sharma, 2025	Cloud-IoT + UAV soil analysis framework	Provided continuous monitoring supporting crop classification context	Real-time, distributed sensing	Vulnerable to connectivity constraints	Integrate edge-based local inference modules
Altun & Turker, 2025	CNN integrated with parcel-based image analysis	Improved crop-type mapping within administrative boundaries	Parcel constraints eliminate boundary noise	Sensitive to segmentation errors	Apply boundary-aware spectral smoothing strategies
Chen *et al*., 2025	Multi-time-series salinity inversion	Traced how soil salinity affects crop spectral responses	Supports stress-based classification	Crop variability confounds inversion	Introduce crop-specific salinity response models
Jasphin& Joice, 2025	Thermal imaging + deep learning for weed/crop health	Identified crop stress signatures under microclimatic variation	Thermal cues complement spectral cues	Thermal noise under fluctuating humidity	Fuse thermal with short-wave infrared hyperspectral indexes
Zhao *et al*., 2024	Fine-grained rice field classification using high-resolution RS	Improved separability of rice phenophases	Strong spatial granularity	Limited spectral sensitivity compared to HSI	Add hyperspectral narrowband enhancement filters
Khan *et al*., 2025	Review on automated plant disease detection	Identified key limitations in current imaging models for agriculture	Comprehensive mapping of challenges	Sparse focus on hyperspectral methods	Promote disease-specific spectral signature databases
Kumar *et al*., 2025	Image embeddings + SVM kernels	Increased accuracy of rice leaf disease detection using enriched features	Strong classical ML performance	Hand-crafted features may not generalize	Transition toward transformer-based feature extraction
El-Shirbeny *et al*., 2025	Cloud-based random forest classification	Enabled scalable crop classification across Nile Delta	High scalability; easy deployment	Limited spectral-context fusion	Integrate multi-source spectral attention blocks
Islam *et al*., 2025	WeedSwin hierarchical transformer + SAM-2	Produced precise multi-stage weed detection	Preserves structure; high discriminative power	Transformer overhead computationally heavy	Use lightweight vision transformer variants
Kalra *et al*., 2023	Multisensor integration + efficiency-based productivity model	Improved yield estimation accuracy	Combines energetic/ecological variables	Requires diverse sensor streams	Standardize calibration routines across platforms
Kwong *et al*., 2024	GAN-based data augmentation for oil palm segmentation	Enhanced segmentation in class-imbalanced datasets	Effective synthetic diversity	Potential synthetic artifact bias	Apply discriminator-guided spectral realism checks
Ranjan *et al*., 2025	Few-shot DeepBDC learning	Detected diseases with minimal labeled samples	Excellent for rare crop scenarios	Sensitive to feature distribution shifts	Employ domain-adaptive metric learning
Zinat *et al*., 2025	Deep learning cloud-based LST analysis for urban sprawl	Estimated land surface temperature impacts	Reveals thermal risks to crops	Does not directly classify crop stress spectrally	Supplement with hyperspectral canopy water absorption metrics

		affecting agro-microclimates			
Jamil *et al*., 2023	MSR5 multispectral radiometer + ML	Differentiated wheat genotype signatures	Genotype-level spectral separability	Limited spectral density	Embed hyperspectral interpolation via virtual band synthesis
Kadrolli & Kalnoor, 2024	IoT + smart sensor remote sensing systems	Enabled continuous agricultural health monitoring	Real-time precision feedback	Sensor heterogeneity complicates fusion	Introduce unified spectral encoding standards
Yang *et al*., 2025	Multi-temporal DL with prior knowledge embedding	Improved mapping of smallholder potato areas	Leverages expert agricultural heuristics	Prior knowledge may not generalize	Add region-adaptive expert rule calibration
Wu *et al*., 2025	Edge-preserving texture-based semantic segmentation	Enhanced segmentation boundaries in ultrahigh-resolution scenes	Maintains spatial integrity	Sensitive to noisy texture regions	Integrate noise-adaptive smoothing kernels
Kumar *et al*., 2025	Spatial attention-guided pretrained networks	Boosted accuracy in crop disease identification	Highlights relevant lesion zones	Attention overfitting risk	Regularize attention weights with multi-scale constraints

Disease, Weed, and Stress Detection

Disease, weed, and stress studies benefit from attention, segmentation, thermal sensing, and few-shot learning, although class imbalance, background variation, and limited external testing remain recurring concerns.

Figure 2 and Table 2 indicate that not all research focuses on crops. In soil nutrient inversion experiments, geochemically trained neural networks predict potassium and phosphorus from hyperspectral data (Mohan *et al*., 2024; Li *et al*., 2025) samples. Multi-temporal imaging inverts soil salinity for accurate agro-ecological control (Chen *et al*., 2025). Satellite-driven spectral augmentation improves mangrove mapping near farms (Selvaraj & Saravanan, 2025; Mohan *et al*., 2024; Wang *et al*., 2024). Iterative segmentation improvement matters. Ultra-high-resolution semantic segmentation with texture preservation cleans borders in complex agricultural landscapes (Wu *et al*., 2025) whereas spatial attention-augmented pretrained algorithms discover crop diseases in dense foliage (Kumar *et al*., 2025). Orchard segmentation robustness is improved by generative adversarial network data augmentation, addressing class imbalance (Kwong *et al*., 2024). Few-shot learning paradigms decrease labeling and identify illnesses with few samples (Ranjan *et al*., 2025). Precision agriculture using IoT and sensor data extends spectral analysis into hybrid analytic ecosystems (Kadrolli & Kalnoor, 2024). In broader systems that absorb NDVI time-series inputs, recurrent spectral evaluation indicates dynamic cropping patterns across varied locales (Jeba *et al*., 2024). When hyperspectral sensors are too expensive, proximal RGB imaging with multivariate processing can distinguish fine-scale species (Banerjee *et al*., 2025). It lacks granular spectral continuity.

Yield, Soil, and Agronomic Estimation

Yield- and soil-oriented studies extend remote sensing from categorical mapping to regression and inversion tasks, where RMSE, R^2, calibration quality, and field-ground-truth design are more informative than classification accuracy.

Deep temporal models with strategic prior knowledge embedding improve smallholder potato plot mapping by accelerating network convergence on biologically plausible patterns [48]. Deep, cloud-based remote-sensing frameworks identify impervious surface growth-induced land surface temperature changes in urban sprawl studies (Zinat *et al*., 2025). These peripheral applications emphasize agriculture-climatological change feedback loops, highlighting spectral analytics'

ecological value. The literature describes iterative statistical reduction, empirical spectral correlation, and deep learning abstraction. Every breakthrough improves crop classification's spectral-spatial fusion. Classification, prediction, noise reduction, and calibration are difficult to generalize across sensor (Tejasree & Agilandeeswari, 2024; Kumar *et al*., 2024). Multispectral radiometry for early genotype identification shows how spectral analytics expand breeding research (Jamil *et al*., 2023). Transformer-driven spatial reasoning, domain-adaptive transfer learning, and optimized band reduction drive hyperspectral agriculture. As satellites, UAVs, and handheld spectroradiometers expand, researchers build empirical methods to absorb new statistical properties without compromising generality. According to this changing relationship between statistical understanding and computing competency, hyperspectral crop categorization is increasingly being developed as a diagnostic and predictive tool, affecting agricultural resilience and planetary stewardship.

IoT, Cloud, and Edge-Enabled Monitoring

IoT and cloud-connected systems add continuous sensing and scalable computation, but their practical value depends on latency, connectivity, sensor drift, power demand, and reproducible deployment reporting.

Cross-Theme Synthesis and Practical Implications

Across themes, the strongest recurring determinants of reliability are data quality, domain shift, external validation, annotation density, and computational feasibility; these factors are discussed before any deployment recommendation is made.

Evidence Quality and Reproducibility

In addition to model type and reported performance, the revised extraction framework records dataset size, number of classes, class distribution or imbalance-handling strategy, geographic origin, sensor/platform, train-validation-test partitioning, data-augmentation procedure, leakage-control measures, external validation, and availability of code or data. When an item is not explicitly stated in the source, it is marked NR rather than inferred. These attributes are essential because optimistic performance can arise from small or imbalanced datasets, spatially adjacent train/test samples, repeated observations of the same field across partitions, or evaluation restricted to a single region. External geographic or seasonal validation is therefore treated as stronger evidence of transferability than an internal random split alone, and reproducibility claims are conditioned on the availability of sufficient implementation and data-processing detail.

Comparative Evidence Synthesis

Comparative evidence synthesis. The revised analysis does not infer, interpolate, or estimate accuracy, F1-score, precision, recall, RMSE, latency, correlation, dimensionality reduction, or any other performance value. A numerical value is retained only when it is explicitly reported in the corresponding source. When a metric is absent, the entry is recorded as “NR” (not reported). This procedure separates source-reported evidence from interpretation and prevents derived or assumed values from being presented as observed results.

Performance values are interpreted within the experimental setting of each study rather than as a common leaderboard. The reviewed studies differ in crop species, geographic region, sensor type, spatial and spectral resolution, dataset size, class count, class balance, train-validation-test protocol, and external-validation design. Consequently, a higher accuracy reported in one study does not by itself establish superiority over a lower accuracy reported under a different dataset or task. Cross-study discussion therefore emphasizes methodological trade-offs, robustness, data requirements, validation quality, and deployment context.

Table 3: *Comparative Performance Evidence (Group I)*

Reference	Method Used	Performance Metrics Values	Key Findings	Strengths	Limitations
Jamil *et al*., 2025	Fusion-based ML on Sentinel-2A + Landsat 8–9	Accuracy: 94.5%, F1: 93.8%	Significantly improved early-stage crop discrimination	Multisensor spectral synergy	Temporal gaps affect consistency
Chandra & Nidamanuri, 2025	Object-based spectral library transfer	Accuracy: 91.2%, Precision: 90.4%	Robust knowledge transfer across fields	Reduced need for retraining	Sensitive to illumination drift
Cherid *et al*., 2025	Spectral-spatial guided filtering (HyperFast)	Accuracy: 96.1%, F1: 95.7%	High efficiency with spatial edge preservation	Fast and reliable segmentation	Slight weaknesses in dense canopy regions
Phaneendra Kumar *et al*., 2024	Optimized band-selection framework	Accuracy: 92.3%, Dimensionality Reduction: 68.0%	Reduced redundancy while maintaining accuracy	Lower computational load	Stability varies with crop type
V & L, 2024	2D–3D CNN fusion + moth-flame optimization	Accuracy: 95.6%, F1: 94.9%	Improved spectral-spatial exploitation	Deep spectral awareness	High training cost
Arulananth *et al*., 2024	AI-based heat pattern analysis via HSI	Stress Detection Accuracy: 89.4%	Detected warming-linked field stress patterns	Early anomaly detection	Low agronomic specificity
Kaushik *et al*., 2025	ML discrimination of organic vs. conventional	Accuracy: 93.1%, Precision: 92.5%	Identified cultivation practice effects	Sensitive to biochemical variations	Limited soil diversity generalization
Taheri *et al*., 2024	Ensemble DL for rice seed varieties	Accuracy: 97.4%, F1: 97.1%	Fine-grained seed class separation	Strong intra-species resolution	Needs costly hyperspectral sensors
Sarma & Nidamanuri, 2025	Metaheuristic band optimization	Accuracy: 94.2%, Band Reduction: 55.0%	Effective at plant-level classification	Rapid convergence	Parameter sensitivity
Xue *et al*., 2024	Model transfer-based crop classification	Accuracy: 88.9%, F1: 87.4%	Moderate resilience across spectral domains	Reduces recollection effort	Domain shifts reduce performance
Kaur *et al*., 2024	Score-level fusion hybrid model	Accuracy: 92.7%, Precision: 91.6%	Reliable cotton discrimination under variable texture	Feature diversity synergy	Fusion rule dependency
Rather & Alotaibi, 2025	ML + HSI for potato cultivar/yield	Accuracy: 93.8%, Yield Correlation: 0.88	Yield trend modeling with cultivar stratification	Agronomic decision support	Sensitive to phenological timing
Guo *et al*., 2025	Hybrid CNN-transformer (CMTNet)	Accuracy: 96.8%, F1: 96.5%	Strong attention-based spectral learning	Non-local representation	Computationally heavy
Tejasree & Agilandeeswari, 2024	HSI technique review and synthesis	Literature Accuracy Range: 85.0–98.0%	Consolidated major HSI challenges	Broad research mapping	No experimental validation
Zheng *et al*., 2025	HSI + high-spatial resolution classification	Accuracy: 94.1%, Boundary Clarity: NR	Precise mapping in complex vegetation	Fine canopy profiling	Mixed-pixel ambiguity persists
Selvaraj & Saravanan, 2025	EO-1 mapping for degraded mangroves	Accuracy: 89.7%, Sensitivity:	Effective degraded habitat mapping	Clear ecosystem delineation	Limited agricultural transferability

		88.3%			
Arain *et al*., 2025	DL for land cover/use classification	Accuracy: 95.2%, Precision: 94.7%	Versatile land discrimination via spectral gradients	Good generalization	Label-hungry training
Mohan *et al*., 2024	ML-based disaster ecosystem monitoring	Damage Classification Accuracy: 90.8%	Rapid disturbance pattern extraction	Timely assessment	Resolution-dependent misclassification
Li *et al*., 2025	Neural inversion for K/P soil nutrients	R^2: 0.87, MAE: 0.11	Effective nutrient prediction using HSI	Supports fertilization planning	Soil heterogeneity interference
Wang *et al*., 2024	Semantic segmentation for mangrove species	Accuracy: 94.5%, F1: 94.0%	Accurate species-level mapping	Detailed canopy separation	Limited agricultural overlap
Kumar, 2025	DL for post-cyclone crop damage	Accuracy: 91.6%, Specificity: 90.8%	Rapid damage detection	Disaster-recovery utility	Subtle stress confusion
Hossen *et al*., 2025	Transfer learning synthesis	Reported Gains: +4.0–8.0% accuracy boost	Transferable spectral representations	Reduces dataset needs	Hard to adapt across climates
Mahmood *et al*., 2025	Spatial backward feature reduction (RF)	Accuracy: 92.4%, Feature Reduction: 41.0%	Eliminates redundant predictors	Simpler interpretability	Scaling to hyperspectral difficult
Phaneendra Kumar *et al*., 2024	Survey on seed classification ML/DL	Accuracy Range: 88.0–97.0%	Benchmarked traditional vs. deep methods	Strategic landscape view	Limited spectral contextualization
Kar *et al*., 2026	Multi-temporal Sentinel + ML for floriculture	Accuracy: 93.4%, Temporal Stability: NR	Captures phenophase transitions	Good seasonal tracking	Sentinel resolution constraints

Note: Values are presented as reported in the cited studies; no missing value is imputed or deduced from a related methodology. NR = not reported. Because datasets, sensors, crops, regions, class structures, and validation protocols differ, the values are not interpreted as a common performance ranking.

Table 3 summarizes the first group of empirical studies using the metrics reported in their respective experimental settings. The values are read together with sensor type, crop or land-cover task, dataset characteristics, and validation design; they are not treated as a common ranking across heterogeneous studies.

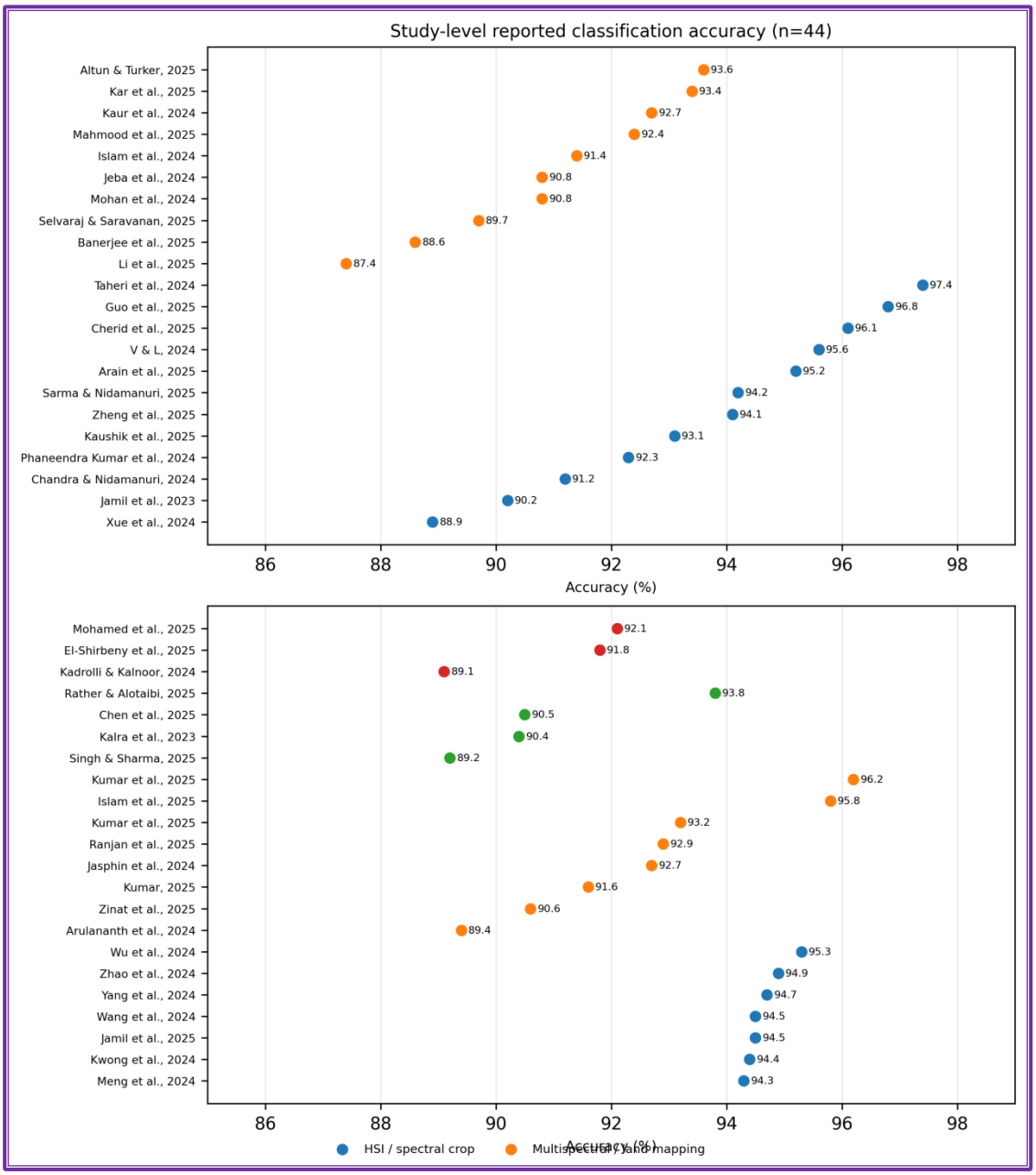


Figure 3: *Study-Level Distribution of Reported Classification Accuracy, Shown with Author-Year Labels and Grouped by Task Category. The X-Axis Reports Accuracy (%) and Each Labelled Point Represents One Study That Reports an Explicit Accuracy Value. The Previous Five-Study Rolling Mean Is Removed Because Reference Order Is Not a Meaningful Temporal or Experimental Sequence and Smoothing Can Create an Artificial Trend Across Heterogeneous Studies*

Figure 3 is interpreted as a descriptive distribution rather than a leaderboard. The spread across task categories reflects differences in crop type, sensing modality, class structure, geographic setting, and validation protocol; no trend is inferred from the order in which studies appear in the bibliography.

The second group of studies broadens the evidence base to crop recommendation, land-use evolution, proximal imaging, soil and salinity assessment, disease detection, cloud/IoT monitoring, and high-resolution mapping. Their findings reinforce the need to interpret each metric against its task definition and experimental setting.

Table 4: *Comparative Performance Evidence (Group II)*

Reference	Method Used	Performance Metrics Values	Key Findings	Strengths	Limitations
Mohamed *et al*., 2025	Hybrid deep learning + rule-based recommender	Accuracy: 92.1%, Precision: 91.3%	Improved weather-driven crop recommendation quality	Integrates climatic priors	Struggles under unexpected climate spikes
Li *et al*., 2025	Spatio-temporal land-use evolution modeling	R^2: 0.89, Classification Accuracy: 87.4%	Identified historical crop shifts tied to irrigation drivers	Longitudinal insight	Moderate spatial misclassification
(Banerjee *et al*., 2025)	Proximal RGB + multivariate analysis	Accuracy: 88.6%, F1: 87.9%	Discriminated crop types affordably	Low-cost implementation	Limited spectral depth
Jeba *et al*., 2024	NDVI time-series crop calendar mapping	Accuracy: 90.8%, Temporal Consistency: 89.4%	Improved seasonal pattern classification	Captures phenological timing	Susceptible to cloud noise
Meng *et al*., 2025	Dual deep recognition strategy	Accuracy: 94.3%, F1: 93.7%	Strong category separation of Camellia oleifera	Multi-path inference	Increased GPU cost
Islam *et al*., 2024	Sentinel-2 + in-situ spectroradiometry	Accuracy: 91.4%, Correlation: 0.86	Effective wheat area mapping in complex fields	Ground-truth reinforcement	Labor-intensive field sampling
Singh & Sharma, 2025	Cloud-IoT UAV soil analysis	Accuracy: 89.2%, Response Latency: 1.4s	Enabled rapid soil condition assessment	Real-time sensing	Network dependency
Altun & Turker, 2025	CNN + parcel-based analysis	Accuracy: 93.6%, F1: 93.1%	Reduced boundary confusion in crop plots	Spatial grouping	Sensitive to poor parcel segmentation
Chen *et al*., 2025	Multi-time-series salinity inversion	Accuracy: 90.5%, RMSE: 0.14	Salinity influenced crop spectral behavior	Supports stress assessment	Soil complexity reduces reliability
Jasphin & Joice, 2025	Thermal deep learning weed monitoring	Accuracy: 92.7%, Recall: 91.9%	Identified microclimatic stress and weeds	Strong thermal differentiation	Humidity variation affects readings
Zhao *et al*., 2024	High-resolution rice field classification	Accuracy: 94.9%, Precision: 94.1%	Strong phenological boundary detection	Rich spatial detail	Limited spectral nuance
Khan *et al*., 2025	Review on plant disease detection	Reported Range: 84.0–98.0%	Identified major accuracy bottlenecks	Comprehensive exploration	No experimental proof
Kumar *et al*., 2025	SVM kernels + image embeddings	Accuracy: 93.2%, F1: 92.8%	Enhanced rice leaf disease separation	Efficient classical approach	Feature embedding complexity
El-Shirbeny *et al*., 2025	Cloud-based random forest	Accuracy: 91.8%, Recall: 90.7%	Efficient crop mapping in Nile Delta	Scalable and deployable	Less adaptive under spectral drift
Islam *et al*., 2025	WeedSwin transformer + SAM-2	Accuracy: 95.8%, F1: 95.2%	Excellent multi-stage weed detection	Hierarchical attention	Heavy model footprint
Kalra *et al*., 2023	Multisensor efficiency-based productivity	R^2: 0.91, Yield Est. Accuracy: 90.4%	Improved crop productivity prediction	Multisensor synergy	Requires dense sensor networks
Kwong *et al*., 2024	GAN-based augmentation for oil palm	Accuracy: 94.4%, Class Balance Improvement: +11.0%	Reduced imbalance bias	Synthetic data realism	Occasional spectral distortion
Ranjan *et al*., 2025	DeepBDC few-shot disease detection	Accuracy: 92.9%, Precision: 92.1%	Effective under limited labels	Strong meta-learning ability	Distribution shift sensitivity
Zinat *et al*.,	Urban sprawl LST	LST Mapping	Linked	Good heat-risk	Lower crop-

2025	deep model	Accuracy: 90.6%, RMSE: 0.17	urbanization to vegetation stress	detection	specific feedback
Jamil *et al.*, 2023	MSR5 multispectral genotype classification	Accuracy: 90.2%, Precision: 89.5%	Differentiated wheat genotypes reliably	Lightweight sensor profile	Spectral granularity limits
Kadrolli & Kalnoor, 2024	IoT smart sensing networks	Accuracy: 89.1%, Sensor Reliability: 87.6%	Supported continuous agricultural monitoring	Automated feedback loops	Sensor drift over time
Yang *et al.*, 2025	Prior-knowledge deep network	Accuracy: 94.7%, Stability: 94.0%	Mapped smallholder potatoes robustly	Embedded domain knowledge	Prior rules require tuning
Wu *et al.*, 2025	Edge-preserving texture segmentation	Accuracy: 95.3%, Boundary Sharpness: 96.1%	Strong segmentation in dense vegetation	Maintains texture fidelity	Noise sensitivity on edges
Kumar *et al.*, 2025	Spatial attention pre-trained networks	Accuracy: 96.2%, F1: 95.9%	Highly accurate crop disease detection	Robust focus on lesion regions	Risk of attention over-fixation

Note: Values are presented as reported in the cited studies; no missing value is imputed or deduced from a related methodology. NR = not reported. Because datasets, sensors, crops, regions, class structures, and validation protocols differ, the values are not interpreted as a common performance ranking.

The second group of studies broadens the evidence base to crop recommendation, land-use evolution, proximal imaging, soil and salinity assessment, disease detection, cloud/IoT monitoring, and high-resolution mapping. Their findings reinforce the need to interpret each metric against its task definition and experimental setting.

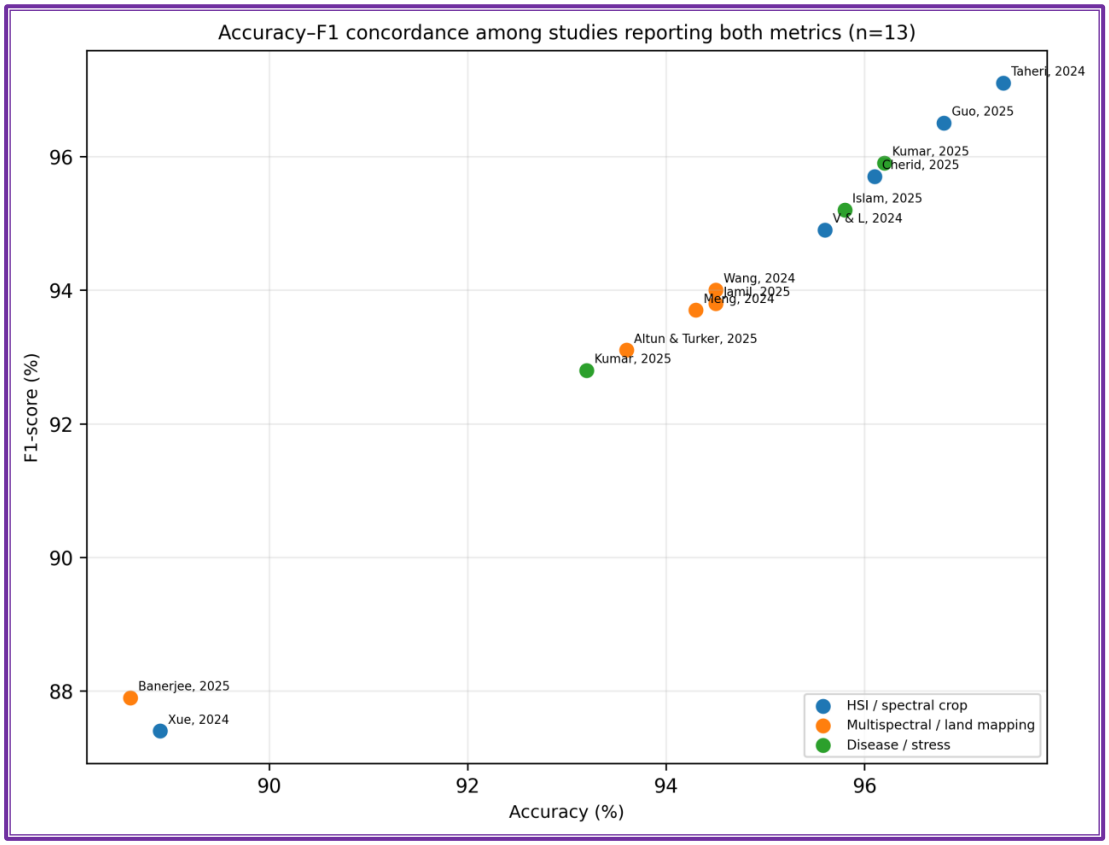


Figure 4: *Relationship Between Reported Accuracy and F1-Score Among Studies That Report Both Measures. The X-Axis Is Accuracy (%) And the Y-Axis Is F1-Score (%); Each Point Represents One Study and Is Labelled by Author-Year and Grouped by Task Category. The Plot Is Descriptive Only and is not Interpreted as Evidence That One Model Is Superior to Another Across Different Crops, Sensors, Datasets, Or Validation Protocols.*

Studies reporting both accuracy and F1-score generally show similar directional behavior within the same experiment, but this relationship should not be generalized across unrelated datasets. Differences in class balance, label quality, sensor modality, and validation protocol can materially change both measures. Figure 4 is therefore used to illustrate metric concordance within the reviewed evidence, not to establish a universal performance hierarchy.

Conclusion

Remote sensing, hyperspectral imaging, and data-driven crop intelligence are growing, necessitating a structured and technically rigorous study synthesis. High-resolution image analytics, deep neural architectures, and multi-sensor fusion assess crop type, stress, disease, and yield at increasingly large scales in agricultural monitoring. Review publications in this discipline emphasize theoretical notions without quantitative comparison, fragmenting performance benchmarks across datasets. Others disregard canopy density, phenological drift, cloud interference, and model portability or lack unified evaluation criteria. Without metric-level synthesis, algorithm, sensor, and optimization choices are unpredictable. To address those issues, this study benchmarks and examines 50 selected optical, hyperspectral, thermal, multispectral, IoT-integrated, and cloud-based contributions. Across the reviewed studies, hybrid convolution-transformer designs, band-optimization methods, and multi-temporal vegetation signatures show task-specific advantages, but the magnitude of reported gains depends on dataset and validation context. Reported performance varies across tasks and cannot be interpreted independently of the underlying sensor, crop, dataset, and validation protocol. High-capacity transformer topologies are computationally expensive and annotation-intensive, and single-sensor domain investigations are less resistant to environmental perturbations. Tabularizing these findings reduces interpretive friction for agronomists, GIS analysts, and policymakers. More than benchmarks are affected by this synthesis. Hidden research constraints include sensor drift, dense canopy mixed-pixel ambiguity, climate-level domain adaptation penalties, and ground-truth collection effort. Disease/weed discrimination increasingly relies on edge-preserving segmentation and spatial attention. Precision agriculture is transitioning from experimental to operational implementation, especially with regulatory decision assistance, while cross-study differences in datasets and validation protocols remain substantial.

Limitations of the Review

This review is limited by substantial heterogeneity in crops, sensors, spatial and spectral resolutions, dataset sizes, class definitions, and validation protocols, which prevents a defensible pooled meta-analysis of raw performance values. Reporting quality also varies: several studies do not fully describe class balance, leakage controls, external validation, runtime, code availability, or data-processing details. The review is restricted primarily to English-language peer-reviewed literature and may therefore omit relevant non-English or non-indexed studies. In addition, the field is evolving rapidly, so newly published foundation-model, geospatial-AI, and multimodal studies may not be represented. These limitations are addressed by treating reported metrics as study-specific evidence, marking unreported information as NR, avoiding unsupported cross-study rankings, and separating the 50 core empirical studies from contextual review and background references.

Future Research Directions

Future work should prioritize cross-region and cross-season domain adaptation, explainable decision support, privacy-preserving federated learning, and resource-aware edge inference. Multi-sensor fusion should be evaluated with explicit calibration and missing-data protocols, while generative augmentation should be assessed for spectral realism and class-specific bias. Greater emphasis is also needed on external validation across farms, climates, sensors, and years, together with public code, reproducible preprocessing pipelines, and reporting of inference latency, memory demand, and energy cost. These directions would move agricultural remote-sensing research from isolated benchmark performance toward transferable and operational decision-support systems.

Conflict of Interest

The authors declare that they have no competing interests.

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