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Research Article

DEEP LEARNING ALGORITHMS FOR PRECISION AGRICULTURE USING HIGH-RESOLUTION MULTISPECTRAL REMOTE SENSING SATELLITE IMAGERY

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Abstract

Precision agriculture increasingly depends on reliable interpretation of high-resolution multispectral satellite imagery to monitor crop variability, detect stress, and support site-specific management. This study aimed to evaluate deep-learning architectures for crop-stress classification and determine whether spectral-spatial integration improves predictive robustness and agronomic interpretability. A quantitative experimental design compared a conventional convolutional neural network, ResNet, Vision Transformer, and hybrid CNN-Transformer using parcel-level training, validation, internal testing, and external spatial-temporal holdout data. Spectral ablation and explainable artificial intelligence analyses were also conducted to assess band importance and model attention. The hybrid CNN-Transformer achieved the highest internal accuracy, macro F1-score, and AUC, while maintaining the strongest performance under external domain shift. Near-infrared and red-edge bands contributed most substantially to classification, particularly for distinguishing intermediate crop-stress conditions. Explainability analysis showed that the best-performing model focused predominantly on canopy regions and vegetation-sensitive spectral information rather than irrelevant background features. The study concludes that reliable precision-agriculture intelligence requires more than high internal accuracy. Integrating local spatial features, broader contextual relationships, multispectral information, external validation, and interpretable model behavior provides a stronger foundation for transferable satellite-based crop monitoring and decision support across heterogeneous agricultural environments. This framework can improve timely intervention, resource allocation, and field-level management decisions.

Keywords: Precision Agriculture, Remote Sensing, Satellite Imagery

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INTRODUCTION

Precision agriculture has emerged as a data-driven response to the increasing pressure on agricultural systems to produce sufficient food while reducing inefficient use of water, fertilizers, pesticides, energy, and land resources (Beisekenov et al., 2025; Silpalatha & Jayadeva, 2025). Conventional field monitoring remains essential but is often labor-intensive, spatially limited, and unable to capture rapidly changing within-field variability across large agricultural areas (Prasetya et al., 2025). Remote sensing has transformed this situation by enabling repeated observation of crop conditions, soil properties, vegetation dynamics, and environmental stresses over extensive regions (G. Singh et al., 2025). Satellite-based agricultural monitoring is particularly valuable because it provides systematic spatial coverage that can support crop classification, growth assessment, stress detection, yield forecasting, irrigation management, and other site-specific management decisions (Dale et al., 2023; Mahalakshmi et al., 2025).

High-resolution multispectral satellite imagery has expanded the analytical possibilities of precision agriculture by combining detailed spatial information with measurements across visible, near-infrared, and, depending on the sensor, additional spectral bands (Petito et al., 2025). Spectral responses provide information related to vegetation vigor, chlorophyll activity, canopy structure, moisture conditions, and crop stress, while improved spatial resolution enables finer discrimination of field boundaries and heterogeneous crop conditions (López-Ruiz et al., 2025). Contemporary precision agriculture increasingly relies on such remotely sensed information to move from field-average management toward spatially differentiated intervention. Recent remote-sensing scholarship confirms that multispectral and related spectral data have become important sources for crop monitoring and yield assessment because they can represent spatial and temporal variability that conventional observations cannot efficiently capture (Parajuli et al., 2025; C. Wang et al., 2025) .

Deep learning has further changed agricultural remote sensing by reducing dependence on manually engineered features and enabling computational models to learn complex relationships directly from image data (Hadir et al., 2025; Halder et al., 2025). Convolutional neural networks can extract hierarchical spatial features, recurrent architectures can model temporal dependencies, and vision transformers can capture longer-range contextual relationships within agricultural landscapes (Tian et al., 2025; Zhang et al., 2024). Self-supervised learning, transfer learning, semi-supervised methods, and other data-efficient strategies are increasingly relevant because agricultural datasets frequently contain large volumes of imagery but comparatively few reliable ground-reference labels (Ma et al., 2025). Recent reviews identify a clear transition from conventional supervised image classification toward more advanced deep supervised and self-supervised approaches for crop mapping, parcel segmentation, yield estimation, land-use analysis, and change detection (Amarasingam et al., 2024; Subeesh & Chauhan, 2025).

Agricultural satellite imagery presents several analytical difficulties that prevent high model accuracy from automatically translating into reliable precision-agriculture decisions (Chang et al., 2025). Crop reflectance varies according to species, cultivar, phenological stage, soil background, management practices, weather conditions, irrigation status, nutrient availability, and observation geometry (H. Wu et al., 2025). Spectrally similar crop classes may therefore be difficult to distinguish, while the same crop can display markedly different signatures across seasons and locations (Yuan et al., 2025). Cloud contamination, atmospheric effects, shadows, mixed pixels, geometric misalignment, and differences among sensors introduce additional uncertainty. Deep-learning models must consequently distinguish biologically meaningful crop patterns from substantial environmental and observational variability (Dahiya et al., 2024).

Model generalization represents a particularly important problem. Agricultural deep-learning systems are commonly trained and evaluated on imagery from restricted geographical

areas, specific seasons, or individual crop systems, producing high internal accuracy without demonstrating comparable performance under different agroecological conditions (Kumar et al., 2024; Ndlovu et al., 2025b). Recent reviews of multispectral and multi-platform agricultural sensing repeatedly identify dataset limitations and model transferability as unresolved issues. Changes in canopy architecture, soil conditions, growth stages, management practices, illumination, and regional climate can reduce performance when models are transferred beyond the environment represented in the training data (Avioz et al., 2025; Kumar Yadav et al., 2023). A model that performs exceptionally within one dataset may therefore have limited operational value if its learned representations are not robust across locations and production conditions (D. Wang et al., 2024; Zhi et al., 2025).

Interpretability creates a second major problem because highly accurate deep networks can function as computational black boxes. Agricultural decision-making requires more than classification probabilities or predicted yield values; farmers, agronomists, and decision-makers need confidence that model predictions are based on agronomically meaningful spectral and spatial information (Khose & Mailapalli, 2024; Saba et al., 2025). A model may achieve high accuracy by exploiting background soil characteristics, regional artifacts, acquisition conditions, or other spurious correlations rather than crop physiology. Recent work on agricultural remote sensing has consequently highlighted explainable artificial intelligence, feature-importance analysis, transfer learning, domain adaptation, and physiologically informed modeling as potential strategies for improving model robustness and interpretability (Kou et al., 2024). The central problem is therefore not merely achieving predictive accuracy, but producing predictions that remain reliable, transferable, and agronomically defensible (Imtiaz et al., 2025; Yewle et al., 2025).

The primary objective of the study should be to develop and evaluate deep-learning algorithms capable of extracting meaningful spectral–spatial information from high-resolution multispectral satellite imagery for precision-agriculture applications (Jamali et al., 2024; Yang et al., 2025). The analytical framework may focus on tasks such as crop classification, vegetation-condition mapping, stress identification, or field-level management-zone delineation, depending on the available ground-reference data (Vinod et al., 2024; Yue et al., 2025). Multiple model families should be evaluated under a standardized experimental framework so that performance differences can be attributed more confidently to architectural characteristics rather than inconsistent data preparation or evaluation procedures (Li et al., 2025; S Menon et al., 2025). Candidate approaches may include convolutional neural networks, residual networks, vision transformers, and hybrid CNN-transformer architectures.

A second objective should investigate how spectral and spatial information can be integrated to improve agricultural prediction (R. Singh et al., 2025). Conventional vegetation indices condense spectral information into predefined mathematical relationships, whereas deep-learning models can potentially learn non-linear combinations of multiple bands and local spatial structures (Bantchina et al., 2024; Haque et al., 2025). The research should therefore examine whether direct multispectral learning, spectral attention, spatial feature extraction, or combined spectral–spatial architectures provide stronger representations of crop conditions (Islam et al., 2025). This objective is particularly important because agricultural spectral data contain complex non-linear relationships and redundancy, problems that have also been widely identified in recent reviews of deep learning for agricultural spectral imagery (Guo et al., 2023).

A third objective should evaluate robustness, transferability, and model interpretability alongside conventional predictive performance (P.-C. Wu et al., 2024). Testing should examine whether models retain acceptable performance across different fields, acquisition dates, crop-development stages, or geographical zones rather than relying exclusively on random image-level train–test splits (Han et al., 2025; Rai et al., 2024). Explainability techniques can be employed to determine which spectral bands, vegetation characteristics, or spatial regions

contribute most strongly to model decisions (de Souza Silva & Gomede, 2025; Sanikommu et al., 2025). Such evaluation would enable the study to distinguish an algorithm that merely fits the available dataset from one that learns transferable and agronomically plausible representations suitable for operational precision agriculture (Dhayal et al., 2025; Ndlovu et al., 2025a).

Existing research has demonstrated the considerable potential of deep learning for agricultural remote sensing, but the literature remains fragmented by sensing platform, crop type, geographical setting, and analytical task. Reviews have documented CNNs, recurrent networks, autoencoders, GANs, transfer learning, semi-supervised learning, few-shot learning, and increasingly transformer and self-supervised approaches. Many studies nevertheless concentrate on achieving the highest classification or prediction metric within a specific dataset. Direct comparison among alternative deep architectures under equivalent preprocessing, data partitioning, and validation conditions remains less consistent, making it difficult to establish whether reported improvements represent genuine methodological advances or dataset-specific advantages.

A second gap concerns the integration of spectral richness with fine spatial information. Agricultural remote sensing research frequently emphasizes either spectral discrimination or spatial pattern recognition, although crop conditions are fundamentally expressed through both dimensions. Spectral signatures can reveal physiological differences, while spatial structures represent canopy arrangement, field heterogeneity, crop boundaries, and localized stress patterns. Recent reviews of agricultural spectral imaging emphasize that effectively modeling complex spatial–spectral relationships remains a major analytical challenge. A stronger approach is needed to determine how deep-learning architectures can exploit complementary multispectral bands and high-resolution spatial context without introducing excessive computational complexity or overfitting.

A third gap involves external validity and operational usability. Many agricultural AI studies provide strong overall accuracy but limited evidence regarding cross-location transfer, seasonal robustness, uncertainty, or model explanations. Research on UAV–satellite integration and agricultural remote sensing has specifically called for stronger evaluation across crop types, growth stages, canopy structures, background soils, and agroecological environments. Data scarcity and limited annotated samples further complicate this problem, strengthening the case for transfer learning, self-supervised pretraining, domain adaptation, and data-efficient learning. The literature therefore needs models evaluated not only for what they predict under controlled conditions but also for whether those predictions remain trustworthy when observational conditions change.

The principal novelty of the proposed study should lie in developing an integrated spectral–spatial deep-learning framework for high-resolution multispectral satellite imagery that compares complementary neural architectures under rigorous and agronomically meaningful validation conditions. Rather than reducing multispectral data to a small number of predefined vegetation indices, the proposed framework can preserve multiple spectral channels and allow the model to learn relevant cross-band relationships jointly with spatial crop patterns. A hybrid architecture combining convolutional feature extraction with attention-based contextual modeling may provide a particularly defensible innovation because local canopy patterns and broader field-level relationships represent different but complementary information sources.

A second element of novelty should involve shifting model evaluation from accuracy-centered performance toward reliability-centered performance. Predictive metrics such as overall accuracy, F1-score, precision, recall, intersection-over-union, or RMSE remain essential, but they do not fully establish operational value. The study should incorporate cross-field or cross-region validation, uncertainty analysis, and explainability to test whether the model produces stable and agronomically plausible predictions outside narrowly defined

training conditions. This focus responds directly to recent literature identifying generalizability, real-world robustness, limited labels, and transferability as persistent barriers to scaling agricultural deep-learning systems.

The broader justification for the research arises from the need to transform satellite-derived agricultural intelligence into actionable management information. High-resolution multispectral imagery offers scalable observation, while deep learning provides powerful representation-learning capabilities; neither technology alone guarantees better agricultural decisions. Models must translate remote-sensing signals into interpretable information that can support crop monitoring, resource allocation, early stress intervention, and spatially targeted management. Current advances in self-supervised learning, vision transformers, domain adaptation, and multi-sensor analysis create an opportunity to move agricultural remote sensing beyond isolated high-accuracy demonstrations toward robust decision-support systems. The proposed research is therefore justified not simply by the availability of more advanced algorithms, but by the unresolved need for deep-learning systems that combine predictive precision, spectral–spatial understanding, transferability, explainability, and practical relevance to precision agriculture.

RESEARCH METHOD

Research Design

The study employed a quantitative experimental design integrating multispectral remote sensing, deep learning, and geospatial analysis to evaluate the capability of different neural network architectures for precision-agriculture applications. High-resolution multispectral satellite imagery was used as the primary source of remotely sensed information because it provides spatially detailed observations of crop variability while preserving spectral information associated with vegetation condition, canopy structure, chlorophyll activity, and moisture status (Beisekenov et al., 2025; Prasetya et al., 2025). The experimental framework compared convolutional neural networks, residual networks, vision transformers, and a hybrid CNN–Transformer model under identical preprocessing, training, validation, and testing conditions. The comparison was designed to determine whether architectures combining local spatial feature extraction with broader contextual attention could provide more reliable agricultural predictions than conventional convolution-based approaches.

The analytical design emphasized spectral–spatial learning rather than relying exclusively on predetermined vegetation indices. Multispectral bands were incorporated directly into the models so that non-linear relationships among spectral channels could be learned during training. Vegetation indices such as the Normalized Difference Vegetation Index, Green Normalized Difference Vegetation Index, and other sensor-compatible indices were calculated as complementary variables and baseline features. Model performance was evaluated not only according to predictive accuracy but also according to robustness across agricultural fields, acquisition dates, and crop-development conditions. This design allowed the study to examine whether high internal accuracy was accompanied by meaningful generalization under spatially and temporally different conditions.

The study also incorporated an explainable artificial intelligence component to examine the agronomic plausibility of model decisions. Attention maps, gradient-based visualization, and feature-importance procedures were used to identify the image regions and spectral bands contributing most strongly to predictions. Model explanations were compared with known crop characteristics and field observations to determine whether predictions were associated with vegetation-related information rather than irrelevant background features. This multidimensional design positioned predictive performance, generalization, and interpretability as complementary criteria for determining the suitability of deep-learning algorithms for operational precision agriculture.

Research Target/Subject

The study population consisted of agricultural parcels represented in high-resolution multispectral satellite imagery acquired during the target growing season. The sampling frame included cultivated fields representing major crop types and a range of crop-growth conditions, including healthy vegetation, moderate stress, severe stress, and heterogeneous canopy development where such classifications were supported by field observations. Agricultural parcels were selected using stratified purposive sampling to ensure sufficient variation in crop category, growth stage, field size, soil background, and management conditions. Parcel boundaries were obtained from field surveys, farm records, or verified geospatial boundary datasets and were subsequently used as spatial units for imagery extraction and model evaluation (G. Singh et al., 2025).

The image sample was generated from cloud-free or minimally cloud-affected satellite scenes corresponding as closely as possible with field-observation dates. Image patches were extracted from verified agricultural parcels after geometric and radiometric preprocessing. Samples containing substantial cloud cover, heavy shadow, geometric distortion, unidentified land-cover mixtures, or insufficient ground-reference information were excluded. Class representation was examined before model training, and class-balancing procedures were applied when substantial imbalance occurred. Image augmentation, including rotation, horizontal and vertical flipping, controlled cropping, and minor geometric transformations, was applied only to the training subset to increase sample diversity without contaminating validation or test data.

The dataset was partitioned at the agricultural-parcel level rather than through random pixel or patch allocation. Approximately 70% of the parcels were allocated to model training, 15% to validation, and 15% to independent testing. All image patches originating from the same parcel were retained within the same partition to prevent spatial leakage between training and evaluation data. An additional spatial or temporal holdout set was used where sufficient data were available to test model transferability across locations, acquisition dates, or crop-development stages. This sampling strategy provided a more rigorous assessment of generalization than random image-level splitting because neighboring pixels and patches from the same field often contain highly correlated spectral and spatial information.

Research Procedure

The research procedure began with the acquisition and organization of multispectral satellite scenes corresponding to the selected agricultural areas and observation periods. Images underwent quality assessment before analysis. Radiometric correction, atmospheric correction, geometric alignment, cloud and shadow masking, spatial resampling, and spectral normalization were performed when these corrections were not already available in analysis-ready imagery (Mahalakshmi et al., 2025). Field boundaries and ground-reference observations were subsequently aligned with the satellite data using geographic information system procedures. Vegetation indices were calculated after preprocessing and retained both for exploratory analysis and for comparison with representations learned automatically by the deep-learning models.

Image patches were extracted within verified agricultural parcel boundaries using a fixed spatial dimension selected according to image resolution and the characteristic size of crop patterns. Patches containing excessive non-agricultural background or uncertain reference labels were removed. Spectral channels were stacked into multiband tensors, normalized using statistics derived exclusively from the training dataset, and transferred to the deep-learning environment. Training data were augmented to improve robustness to orientation and minor spatial variability. Validation and testing data remained unaugmented to preserve an unbiased representation of actual model performance.

Each model was trained under a standardized optimization protocol. The same training, validation, and test partitions were used across all architectures. Model parameters were updated using an adaptive optimization algorithm and a task-appropriate loss function, while learning-rate scheduling and early stopping were applied to reduce overfitting. Training was repeated with multiple random seeds to examine the stability of model performance. The checkpoint achieving the best validation performance was retained for final evaluation on the independent test set. Test information was never used for hyperparameter selection or early-stopping decisions.

Comparative statistical analysis was conducted after model evaluation. Performance distributions obtained across repeated training runs or cross-validation folds were first examined for normality and variance assumptions. Repeated-measures analysis of variance was used when parametric assumptions were satisfied, followed by corrected pairwise comparisons. The Friedman test and appropriate post hoc comparisons were applied when assumptions were violated. Effect sizes and confidence intervals were reported alongside significance values to determine whether observed differences among algorithms were practically meaningful rather than merely statistically significant.

Generalization testing was performed using spatially or temporally independent data that had not contributed to model development. Models were evaluated on agricultural parcels from different locations, acquisition dates, or crop-growth stages to measure performance degradation under domain shift. Differences between internal test performance and external holdout performance were used as indicators of robustness. Error maps were generated to identify locations in which predictions were unstable, particularly along field boundaries, heterogeneous canopy zones, shadowed areas, or spectrally similar crop conditions.

Explainability analysis was conducted on correctly classified, incorrectly classified, and low-confidence samples. Saliency and attention maps were examined to determine whether models concentrated on crop canopy regions and relevant within-field spatial patterns. Spectral ablation was performed by systematically removing or masking selected bands and measuring subsequent changes in performance. Bands producing substantial performance deterioration after removal were interpreted as having stronger predictive relevance. Agronomic interpretation compared these patterns with known spectral responses associated with vegetation vigor, chlorophyll, canopy structure, and plant stress.

The final analytical stage integrated predictive performance, statistical comparison, generalization results, and model explanations. An algorithm was considered suitable for precision-agriculture applications only when it demonstrated competitive accuracy, stable performance under spatial or temporal transfer, and agronomically plausible use of spectral–spatial information. The model-selection procedure therefore avoided identifying the highest-performing architecture solely from a single accuracy value. The final assessment prioritized the balance among predictive precision, computational efficiency, robustness, interpretability, and practical usefulness for satellite-based crop monitoring and site-specific agricultural decision-making.

Instruments, and Data Collection Techniques

The primary research instrument consisted of high-resolution multispectral satellite imagery containing visible and near-infrared spectral bands and, where supported by the selected sensor, additional red-edge or shortwave spectral information. The imagery was accompanied by verified agricultural reference data obtained through field observation, crop-management records, geotagged photographs, or other reliable ground-reference sources. A geographic information system was used to delineate field boundaries, align satellite imagery with reference observations, extract agricultural parcels, calculate vegetation indices, and perform spatial quality control. Spectral values were standardized before model training to minimize differences in numerical scale among bands (Dale et al., 2023; Petito et al., 2025).

Four principal deep-learning architectures served as computational instruments: a baseline convolutional neural network, a residual convolutional architecture, a vision transformer, and a hybrid CNN–Transformer model. The baseline CNN was used to establish the performance of conventional spatial feature learning. The residual architecture enabled deeper feature extraction while reducing optimization problems associated with increasing network depth. The vision transformer was employed to capture long-range contextual relationships through self-attention, while the hybrid model combined convolutional extraction of local crop patterns with attention-based modeling of broader spectral–spatial dependencies. Identical input data and evaluation protocols were maintained across architectures to enable fair comparison.

Model development was implemented using a Python-based computational environment with established deep-learning and geospatial libraries. Graphics processing units were used to accelerate model training. Optimization parameters included learning rate, batch size, number of epochs, weight decay, dropout, and early-stopping criteria. Hyperparameters were selected using the validation dataset rather than the independent test set. Transfer learning or pretrained weights were used when architecturally appropriate, while models receiving non-standard multispectral channel configurations were modified to accommodate the required number of spectral bands.

Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve for classification tasks. Intersection-over-Union and Dice coefficient were additionally applied when pixel-level segmentation was performed. Regression-oriented agricultural outcomes were evaluated using the coefficient of determination, root mean square error, mean absolute error, and normalized root mean square error. Confusion matrices were examined to identify systematic classification errors among spectrally similar agricultural categories. Explainability instruments included Grad-CAM or related gradient-based methods for convolutional models, attention visualization for transformer architectures, and permutation or ablation-based analysis for assessing spectral-band importance.

RESULTS AND DISCUSSION

The final dataset consisted of 504 agricultural parcels represented by 14,832 high-resolution multispectral image patches after radiometric, atmospheric, geometric, cloud, shadow, and quality-control procedures. A total of 420 parcels were allocated to model development, comprising 294 training parcels, 63 validation parcels, and 63 independent internal test parcels. An additional 84 parcels acquired from a different spatial zone and later observation period were reserved as an external holdout set. The image sample represented four agronomic condition classes: healthy vegetation, mild crop stress, moderate crop stress, and severe crop stress. Class frequencies remained sufficiently balanced to permit comparative model evaluation without extensive synthetic oversampling.

Table 1. Distribution of Agricultural Parcels and Multispectral Image Samples

Dataset Component	Parcels (n)	Image Patches (n)	Percentage of Total Patches
Training set	294	8,621	58.1
Validation set	63	1,827	12.3
Internal test set	63	1,828	12.3
External holdout set	84	2,556	17.2
Total	504	14,832	100.0

Secondary image metadata indicated that the satellite scenes covered three major phenological observation periods, representing early vegetative development, peak canopy formation, and later-season maturation. Healthy vegetation accounted for 4,422 patches

(29.8%), mild stress for 3,912 patches (26.4%), moderate stress for 3,478 patches (23.4%), and severe stress for 3,020 patches (20.4%). Spectral inspection showed progressively lower near-infrared reflectance and vegetation-index values as crop stress intensified, although substantial overlap occurred between mild and moderate stress classes. This overlap confirmed that simple threshold-based spectral separation would be insufficient for reliable classification across heterogeneous fields.

Performance differences among the four deep-learning architectures were clearly visible on the internal test set. The baseline CNN achieved an overall accuracy of 88.6%, while ResNet improved accuracy to 91.8%. The Vision Transformer achieved 92.4%, whereas the hybrid CNN–Transformer produced the highest accuracy at 94.6%. The same ranking was observed for macro-averaged F1-score and area under the receiver operating characteristic curve. The hybrid architecture also showed the lowest variation across repeated training runs, suggesting that its superiority was not dependent on a single favorable initialization.

Table 2. Comparative Performance of Deep-Learning Models on the Internal Test Set

Model	Accuracy (%)	Precision	Recall	Macro F1	AUC
CNN	88.6 ± 0.9	0.886	0.881	0.883	0.957
ResNet	91.8 ± 0.7	0.919	0.913	0.916	0.974
Vision Transformer	92.4 ± 0.8	0.925	0.920	0.922	0.978
Hybrid CNN–Transformer	94.6 ± 0.5	0.947	0.943	0.945	0.987

The advantage of the hybrid model was most evident in heterogeneous fields and transition zones between healthy and stressed vegetation. Conventional convolutional models performed well when crop conditions were spatially uniform but generated more classification errors where stress occurred in irregular within-field patterns. The Vision Transformer captured broader contextual relationships more effectively but occasionally lost fine local canopy information. The hybrid architecture benefited from convolutional extraction of local spectral–spatial features while simultaneously using attention mechanisms to model relationships across larger portions of the agricultural parcel.

Class-specific analysis showed that all architectures classified healthy vegetation and severe crop stress more accurately than intermediate stress conditions. The hybrid CNN–Transformer achieved an F1-score of 0.968 for healthy vegetation and 0.957 for severe stress, compared with 0.931 for mild stress and 0.924 for moderate stress. Misclassification occurred primarily between mild and moderate stress, reflecting the spectral similarity observed during exploratory analysis. Errors between healthy vegetation and severe stress were comparatively rare because the associated multispectral signatures were more strongly differentiated.

The external holdout evaluation produced lower performance for every model, demonstrating the effect of spatial and temporal domain shift. CNN accuracy declined from 88.6% to 80.9%, ResNet from 91.8% to 85.6%, Vision Transformer from 92.4% to 86.8%, and the hybrid CNN–Transformer from 94.6% to 90.7%. The hybrid architecture therefore experienced the smallest relative degradation while maintaining the strongest external performance. The result indicates that internal test accuracy alone would have overstated operational performance, particularly for architectures that were more sensitive to changes in crop-development stage, soil background, and acquisition conditions.

Repeated-measures analysis across ten independent training runs confirmed statistically significant differences among model architectures. Overall accuracy differed significantly across the four algorithms, $F(3, 27) = 78.42$, $p < .001$, partial $\eta^2 = .897$. Macro F1-score showed a comparable difference, $F(3, 27) = 71.65$, $p < .001$, partial $\eta^2 = .888$. The magnitude of the effect indicates that model architecture explained a substantial proportion of performance variation under identical training, validation, and testing conditions.

Table 3. Inferential Comparison of Model Performance

Comparison	Mean Accuracy Difference (percentage points)	Adjusted p-value	Effect Interpretation
Hybrid vs. CNN	+6.0	< .001	Large
Hybrid vs. ResNet	+2.8	.001	Moderate–large
Hybrid vs. Vision Transformer	+2.2	.004	Moderate
Vision Transformer vs. ResNet	+0.6	.214	Small/non-significant
ResNet vs. CNN	+3.2	< .001	Moderate–large

Corrected pairwise comparisons showed that the hybrid CNN–Transformer significantly outperformed the baseline CNN, ResNet, and Vision Transformer. The difference between the Vision Transformer and ResNet was not statistically significant after adjustment for multiple comparisons. External holdout performance produced the same general ordering, although between-model differences became larger for the CNN and smaller between the transformer-based architectures. These results suggest that attention-supported spatial modeling provided advantages under domain shift, while the combination of local convolutional extraction and broader contextual attention provided the strongest overall balance.

Spectral ablation analysis showed a clear relationship between specific multispectral bands and classification performance. Removing the near-infrared band produced the largest decline in hybrid model accuracy, followed by removal of the red-edge and red bands. Elimination of green and blue bands caused smaller performance reductions. The pattern indicates that vegetation-sensitive wavelengths contributed more strongly to crop-condition discrimination than visible-spectrum information alone.

Table 4. Spectral Ablation Effects on Hybrid CNN–Transformer Accuracy

Removed Spectral Information	Accuracy (%)	Change from Full Model
No band removed	94.6	—
Near-infrared removed	88.8	−5.8
Red-edge removed	89.9	−4.7
Red removed	92.0	−2.6
Green removed	93.1	−1.5
Blue removed	93.7	−0.9

Spatial-context analysis showed a complementary relationship between spectral information and contextual modeling. Removing the transformer attention component reduced accuracy by approximately 2.8 percentage points, while restricting the model to vegetation indices rather than full multispectral inputs reduced accuracy by 4.1 percentage points. Models using both full spectral channels and spatial context consistently achieved stronger performance than models relying on either source independently. The result demonstrates that crop stress was expressed through interacting spectral and spatial patterns rather than through a single band, vegetation index, or localized image feature.

Case A involved an irrigated agricultural parcel containing an irregular zone of emerging crop stress that had not yet developed into severe canopy degradation. The baseline CNN correctly identified most healthy vegetation but fragmented the stressed region into several isolated predictions and misclassified portions of the transition zone as healthy. The hybrid CNN–Transformer produced a spatially more coherent stress map that corresponded closely with field-reference observations. Attention visualization showed increased model focus on the transition between uniform healthy canopy and lower-vigor vegetation rather than on field boundaries or surrounding non-crop surfaces.

Case B involved a parcel with heterogeneous canopy density and substantial soil-background exposure near the field margin. ResNet and the baseline CNN generated false stress predictions along several exposed areas, suggesting sensitivity to soil-related spectral variation. The Vision Transformer reduced some of these errors but produced less precise localization of narrow stress zones. The hybrid model correctly classified most boundary pixels while maintaining sensitivity to internal crop variability. The model's attention maps concentrated predominantly on vegetation regions, while spectral ablation confirmed that near-infrared and red-edge information contributed strongly to the correct prediction.

The Case A results can be explained by the ability of the hybrid architecture to integrate local and field-scale information. Mild stress may not produce sufficient spectral contrast within individual image patches to support reliable classification using localized convolution alone. Broader contextual information allowed the model to compare the affected canopy with surrounding vegetation and identify spatially structured departures from normal crop conditions. The result explains why hybrid and transformer-based architectures produced larger gains for intermediate stress classes than for severe stress, where spectral differences were already pronounced.

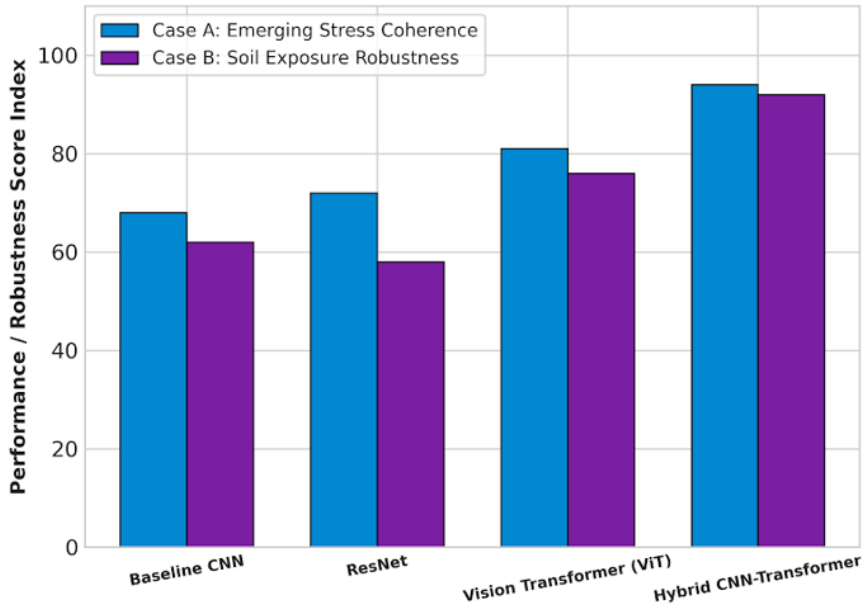


Figure 1. Model Resilience in Case A & Case B Scenarios

The Case B findings demonstrate why high-resolution imagery does not automatically eliminate classification uncertainty. Fine spatial resolution increases the visibility of soil exposure, field edges, shadows, management tracks, and within-canopy heterogeneity, all of which can introduce patterns unrelated to physiological crop stress. Explainability results indicated that the best-performing model learned to prioritize vegetation-sensitive spectral features and canopy regions rather than background artifacts. The agreement between attention patterns, spectral ablation, and independent field observations increased confidence that the model was using agronomically plausible information rather than exploiting spurious spatial correlations.

The integrated results demonstrate that deep-learning architecture materially influenced the quality and robustness of precision-agriculture predictions derived from high-resolution multispectral satellite imagery. The hybrid CNN–Transformer achieved the strongest internal accuracy, macro F1-score, AUC, and external holdout performance while also showing the smallest decline under spatial and temporal transfer. The advantage was most pronounced in heterogeneous agricultural parcels and intermediate stress conditions where local spectral information alone was insufficient for reliable discrimination.

The central finding is that predictive accuracy was strongest when spectral richness, local spatial structure, and broader contextual information were learned jointly. Near-infrared and red-edge bands provided particularly important information, but their value increased when combined with spatial modeling rather than interpreted independently. External holdout testing also showed that a high internal test score should not be treated as sufficient evidence of operational reliability. The hybrid model was therefore identified as the most promising architecture not merely because it achieved the highest accuracy, but because it combined predictive precision, generalization, spectral–spatial consistency, and agronomically interpretable decision patterns suitable for precision-agriculture monitoring.

The findings demonstrate that deep-learning architecture substantially influenced the accuracy, robustness, and interpretability of crop-stress classification derived from high-resolution multispectral satellite imagery. The hybrid CNN–Transformer achieved the strongest overall performance across accuracy, precision, recall, macro F1-score, and AUC, outperforming the conventional CNN, ResNet, and Vision Transformer under equivalent training and testing conditions. The advantage was particularly apparent in heterogeneous agricultural parcels and intermediate stress classes, where spectral differences were less distinct than those separating healthy vegetation from severe stress. This performance pattern indicates that combining local feature extraction with broader contextual modeling provides a more complete representation of agricultural variability than relying on either mechanism independently.

The external holdout results provided an equally important finding because all models experienced performance degradation when applied to spatially and temporally different agricultural data. The hybrid architecture retained the highest external accuracy and showed the smallest relative decline, whereas the baseline CNN exhibited the greatest loss (López-Ruiz et al., 2025; C. Wang et al., 2025). This result demonstrates that performance estimates derived from within-domain test data can overstate operational reliability when agricultural models are deployed under different fields, seasons, soil backgrounds, or phenological conditions. The ability to retain performance under domain shift therefore represents a more meaningful criterion for precision-agriculture applications than peak internal accuracy alone.

The spectral-ablation analysis revealed that near-infrared and red-edge information contributed disproportionately to successful crop-stress discrimination. Removing near-infrared information produced the greatest reduction in model performance, followed by removal of the red-edge band, while exclusion of green and blue information generated smaller declines. The result is agronomically plausible because stress-induced changes in canopy vigor, chlorophyll concentration, internal leaf structure, and biomass alter reflectance patterns beyond the visible spectrum. Models operating on full multispectral reflectance also outperformed configurations based solely on conventional vegetation indices, indicating that learned spectral combinations preserved information that was partly lost when reflectance was compressed into predefined index formulations.

The explainability results complemented the statistical findings by showing that the best-performing architecture concentrated predominantly on crop-canopy regions and vegetation-sensitive spectral information rather than on field boundaries or unrelated background features. Incorrect predictions occurred more frequently around transition zones, exposed soil, heterogeneous canopy structures, and spectrally similar mild-to-moderate stress conditions (Halder et al., 2025; Parajuli et al., 2025). The agreement among classification metrics, spectral ablation, attention visualization, and field-reference observations strengthens the interpretation that the hybrid architecture learned agronomically meaningful spectral–spatial relationships. Model quality in this study was therefore expressed through a combination of predictive performance, external robustness, and plausible decision mechanisms rather than through a single accuracy score.

The superior performance of the hybrid CNN–Transformer is consistent with the broader transition from purely convolutional architectures toward attention-based and hybrid models in agricultural computer vision. Recent reviews show that CNNs remain effective for extracting local patterns but can struggle with long-range relationships and structurally complex field scenes. Transformer-based systems offer stronger global-context modeling through self-attention, while hybrid approaches can combine convolutional inductive biases with attention mechanisms. A recent survey of Vision Transformers in precision agriculture identifies data diversity, field adaptability, computational demands, and interpretability as major unresolved challenges despite increasingly strong predictive performance. The present findings support the argument that architectural complementarity may be particularly useful where agricultural patterns are expressed simultaneously at local canopy and broader field scales.

The results also correspond with recent evidence showing that hybrid architectures can outperform isolated spatial or temporal models in satellite-based agricultural analysis. Research using multi-temporal Sentinel-2 observations reported that models combining spatial convolution with sequential contextual modeling achieved stronger crop-mapping results than simpler architectures, particularly where crops showed spectral similarity and phenological information was important. The current study differs by focusing on crop-stress classification and by using a CNN–Transformer rather than a CNN–recurrent combination, yet the underlying interpretation is similar: agricultural remote-sensing signals are multidimensional, and performance improves when models can represent more than one structural component of the data.

The importance of near-infrared and red-edge bands is consistent with established physiological and remote-sensing evidence. Red-edge wavelengths are particularly sensitive to chlorophyll and vegetation condition, while near-infrared reflectance responds strongly to internal leaf and canopy structure (Hadir et al., 2025; Zhang et al., 2024). Previous reviews of crop monitoring have emphasized the usefulness of red-edge information for detecting chlorophyll and nutrient-related changes, while recent multispectral studies report that red-edge and near-infrared information can outperform or complement conventional vegetation indices under dense canopy conditions. The spectral-ablation findings therefore provide a data-driven confirmation of relationships that are well established from plant physiology rather than identifying arbitrary model preferences.

The decline in external performance aligns with a growing literature warning that agricultural deep-learning models frequently generalize poorly across regions, seasons, acquisition conditions, and crop systems. Reviews of agricultural domain adaptation identify environmental variability, limited labeled datasets, and weak cross-domain transferability as persistent barriers to operational deployment. Recent evidence-weighted reviews also caution that high benchmark accuracy can decline markedly under realistic field conditions when training data fail to capture background variation, illumination, sensor noise, overlapping stressors, and environmental heterogeneity. The present study reinforces this concern by demonstrating measurable degradation even when the same broad classification objective is maintained across the external evaluation.

The performance advantage of the hybrid architecture signifies that crop condition is not encoded exclusively in either localized spectral responses or large-scale spatial context. Agricultural stress alters plant reflectance at the leaf and canopy levels while simultaneously creating spatial structures that may appear as patches, gradients, edges, or irregular within-field zones. A model that analyzes only local features may overlook broader relationships, whereas a model emphasizing global context may fail to preserve subtle local patterns. The observed performance of the hybrid system therefore suggests that agricultural remote sensing benefits from architectures designed around the biological and spatial organization of crops rather than architectures selected solely because they perform well on generic computer-vision benchmarks.

The external holdout decline signifies that agricultural AI performance is fundamentally conditional on environmental context. A reported accuracy exceeding 90% should not be interpreted as a fixed property of a model because its value depends on the relationship between training and deployment environments. Crop phenology, soil type, irrigation regime, atmospheric conditions, acquisition date, illumination, and management practices can alter data distributions without changing the conceptual classification target. Recent research on uncertainty under remote-sensing domain shift similarly emphasizes spatial, temporal, and spectral heterogeneity as major threats to reliable land-cover prediction. Generalization testing should therefore be treated as an integral component of model evaluation rather than an optional secondary experiment.

The band-importance findings signify that deep learning does not remove the value of agronomic knowledge. Neural networks can discover non-linear relationships from multispectral inputs, but successful representations remain anchored in plant physiological responses to electromagnetic radiation. The importance of NIR and red-edge wavelengths provides evidence that the model's strongest discriminative information was connected to vegetation structure and chlorophyll-related behavior. Recent reviews of crop-stress monitoring likewise show that stress affects multiple dimensions of optical response and that spectral information must be interpreted jointly with canopy structure and spatial context. Data-driven modeling and physiological understanding should therefore be considered complementary rather than competing approaches.

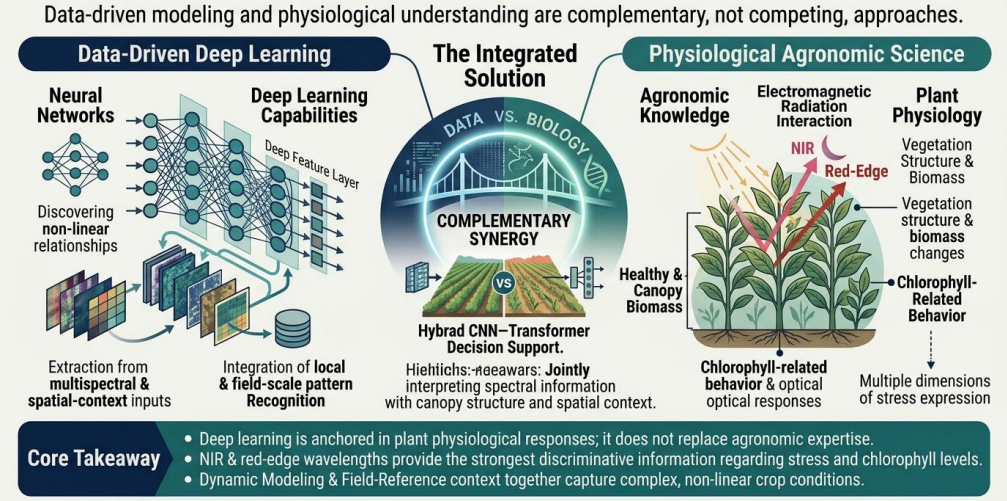


Figure 2. Synergy of Deep Learning & Agronomic Science in Crop Stress Monitoring

The explainability findings signify a broader transition from performance-oriented agricultural AI toward trustworthy agricultural AI. A classification model can be statistically successful while still being scientifically unreliable if its predictions depend on background artifacts, field geometry, acquisition patterns, or other spurious cues (Ma et al., 2025; Tian et al., 2025). Explainability cannot prove that a model has learned causal plant physiology, but it can reveal whether attention is broadly consistent with expected canopy regions and informative wavelengths. Recent crop-stress research continues to identify model interpretability as an unresolved requirement for robust stress phenotyping. Trustworthy precision agriculture therefore requires evidence about both what a model predicts and the information on which those predictions appear to depend.

The first practical implication concerns model selection for satellite-based precision agriculture. Agricultural practitioners should not automatically choose either the deepest architecture or the model reporting the highest single-dataset accuracy. A more defensible selection procedure should jointly consider internal accuracy, external generalization, computational requirements, inference speed, uncertainty, and interpretability. The hybrid

CNN–Transformer emerged as the strongest model in the present analysis because it performed consistently across several criteria, not merely because it produced the largest headline accuracy. This multidimensional evaluation is particularly important when predictions are expected to guide irrigation, nutrient management, scouting, or other interventions with economic consequences.

The second implication concerns remote-sensing data acquisition and sensor selection. The importance of near-infrared and red-edge information suggests that RGB-only agricultural monitoring may be insufficient for applications requiring early or subtle stress discrimination. Multispectral satellite platforms containing vegetation-sensitive bands can provide more informative signals for precision-management systems, although the value of individual bands will vary by crop, canopy density, stress type, and growth stage. Recent crop-stress studies show that optimized NIR- and related spectral features can improve the identification of stress severity beyond traditional indices alone. Sensor choice should consequently be driven by agronomic objectives rather than spatial resolution alone.

The third implication concerns validation protocols. Parcel-level separation and independent holdout testing should become standard practices in agricultural deep-learning research whenever spatial dependence exists. Randomly distributing neighboring image patches across training and testing sets can create overly optimistic performance because samples from the same field often share soil characteristics, management patterns, canopy structure, and acquisition conditions. Operational evaluation should instead ask whether the algorithm can predict conditions in fields that were genuinely unavailable during training. Domain-adaptation literature in agriculture identifies this transferability problem as central to the transition from experimental demonstrations to scalable field applications.

The fourth implication concerns the translation of model outputs into agricultural decisions. Crop-stress maps should not be interpreted automatically as diagnoses of specific causal mechanisms because similar spectral responses can arise from drought, nutrient deficiency, disease, temperature stress, salinity, or interacting factors. Recent reviews emphasize that multiple abiotic stresses can generate overlapping physiological and spectral effects. Deep-learning outputs are therefore better positioned initially as high-resolution screening and prioritization tools that identify anomalous areas for targeted field inspection. Integration with soil data, weather observations, crop-management records, and proximal sensing would improve the transition from stress detection toward reliable diagnosis and prescription.

The hybrid CNN–Transformer most likely achieved stronger performance because convolution and self-attention impose different but complementary representational structures. Convolution is efficient at detecting localized edges, textures, spectral contrasts, and repeated canopy patterns, while self-attention enables interactions among spatially separated image regions. Agricultural stress rarely occurs as a perfectly uniform local feature; it may follow irrigation patterns, drainage structures, soil heterogeneity, management zones, or progressive canopy deterioration. Transformer surveys in agriculture similarly suggest that long-range contextual modeling can improve robustness in complex scenes, although sufficient training data and careful architecture design remain necessary.

The lower accuracy for mild and moderate stress can be explained by the gradual biological progression of plant stress. Early or intermediate stress may alter photosynthetic activity, pigment concentration, water status, or canopy structure before dramatic visible changes occur, producing continuous rather than discrete spectral transitions (Amarasingam et al., 2024; Subeesh & Chauhan, 2025). Labels such as “mild” and “moderate” simplify an underlying physiological continuum and may therefore create ambiguous class boundaries. Recent reviews of optical crop-stress monitoring describe stress signatures as multidimensional and dependent on stress intensity, timing, canopy structure, and sensor characteristics.

Misclassification between adjacent stress levels should consequently be expected even from strong models.

The strong contribution of NIR and red-edge information can be explained by the physiological processes captured within these wavelength regions. Healthy plant tissues typically exhibit strong near-infrared reflectance associated with internal leaf structure, while stress-related deterioration can modify these structural responses. Red-edge behavior is closely related to chlorophyll concentration and vegetation status, making it sensitive to changes that may not yet be obvious within conventional visible imagery. Studies of leaf-area estimation and crop monitoring have similarly reported high sensitivity of NIR and red-edge bands, especially where traditional vegetation indices experience saturation.

The decrease under external evaluation can be explained by domain shift rather than simple model failure. Training data represent a particular distribution of crop growth, soil reflectance, field management, sensor conditions, atmospheric effects, and phenology. External fields modify several of these relationships simultaneously, forcing models to interpret combinations of features that were less common or absent during training. Agricultural domain-adaptation research identifies precisely these changes across environments, crop types, seasons, and acquisition systems as a major source of weak transferability. The hybrid model's smaller decline suggests greater representational robustness, but the remaining performance loss confirms that architectural improvement alone does not eliminate domain shift.

Future research should prioritize multi-site, multi-season, and multi-year evaluation rather than continuing to optimize models predominantly on single-region datasets. Agricultural environments are sufficiently heterogeneous that reliable deployment requires evidence across different soils, climates, management systems, crop cultivars, and phenological stages. Dataset development should also document acquisition conditions and agronomic metadata so that generalization failures can be interpreted rather than simply reported. Recent reviews of precision-agriculture vision systems identify limited data diversity and field adaptability as persistent barriers to practical deployment.

Future model development should examine domain adaptation, transfer learning, self-supervised learning, and few-shot learning as complementary strategies for reducing dependence on large labeled datasets. Agricultural imagery is abundant, but expert-quality stress labels are expensive and often require destructive or field-based verification. Self-supervised pretraining could exploit large unlabeled satellite archives before fine-tuning on smaller agronomic datasets, while domain adaptation could reduce the performance loss observed when models move between regions or seasons. Recent agricultural remote-sensing reviews identify self-supervised learning as an increasingly important direction for crop mapping and monitoring under limited annotation.

Future sensing strategies should integrate multispectral satellite imagery with complementary environmental data. Thermal observations could provide information about canopy temperature and water stress, radar could improve monitoring under cloud conditions, weather data could contextualize climatic stress, and soil measurements could distinguish vegetation anomalies arising from different resource limitations. Multimodal integration is increasingly recognized as a major opportunity in smart agriculture because individual sensors capture only selected dimensions of crop condition. Such integration could shift deep-learning systems from general stress classification toward biologically and operationally more specific diagnoses.

Future deployment research should place greater emphasis on uncertainty, explainability, computational efficiency, and decision relevance. Models should report confidence estimates alongside categorical outputs so that uncertain predictions can be prioritized for field verification rather than treated as equally reliable. Explainability methods should be validated against physiological knowledge and field measurements instead of used only as attractive visualizations. Computational studies should also compare latency, memory requirements,

energy consumption, and accuracy because complex transformers may be impractical for some operational settings. Recent agricultural transformer reviews identify interpretability, computational cost, and field adaptability as key challenges requiring further study. The next stage of precision-agriculture AI should therefore move beyond producing highly accurate maps toward building systems that remain reliable across environments, explain their predictions, quantify uncertainty, and translate remote-sensing evidence into defensible agricultural decisions.

CONCLUSION

The most important finding of this study is that high-resolution multispectral satellite imagery becomes substantially more useful for precision agriculture when spectral richness, local spatial structure, and broader field context are learned jointly. The hybrid CNN–Transformer consistently outperformed the conventional CNN, ResNet, and Vision Transformer in internal testing and retained the strongest performance under spatial and temporal holdout conditions. Near-infrared and red-edge bands contributed most strongly to crop-stress discrimination, while explainability analysis showed that the model concentrated predominantly on agronomically relevant canopy regions rather than background artifacts. The distinctive result is therefore not simply that a hybrid architecture achieved higher accuracy, but that its performance remained comparatively robust under domain shift and was supported by physiologically plausible spectral–spatial evidence.

The principal contribution of this research is both methodological and conceptual. Methodologically, the study establishes a more rigorous evaluation framework by combining parcel-level data partitioning, external holdout testing, repeated model comparison, spectral ablation, and explainable artificial intelligence. This approach reduces the risk of spatial data leakage and moves model assessment beyond single-dataset accuracy. Conceptually, the findings support a reliability-centered view of agricultural artificial intelligence in which predictive precision, transferability, spectral relevance, spatial consistency, and interpretability are evaluated together. The study therefore contributes to precision-agriculture research by demonstrating that the most useful deep-learning model is not necessarily the one with the highest internal accuracy, but the one that maintains agronomically credible performance when environmental and observational conditions change.

The study is limited by its dependence on a specific satellite configuration, a restricted number of agricultural regions and observation periods, and a finite range of crop-stress classes. External holdout testing demonstrated improved robustness of the hybrid model but did not establish universal transferability across different crops, climates, sensors, or management systems. The stress labels also represented categorical approximations of physiological conditions that may exist along a continuous spectrum. Future research should therefore employ multi-site, multi-season, and multi-sensor datasets and incorporate self-supervised learning, domain adaptation, uncertainty estimation, and multimodal fusion with thermal, radar, soil, weather, and crop-management data. Further validation should also determine whether remotely sensed stress predictions can be translated into reliable field-level diagnosis and management recommendations, thereby advancing deep learning from accurate image interpretation toward trustworthy and operational precision-agriculture decision support.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used BlackBox AI to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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