International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 15, Issue 6 [June 2026] PP: 208-213

A Review of the Application of Unmanned Aerial Vehicles in Agricultural Pest Detection

Da Cong, He Zhang, Xiaoyu Lin
School of Management, Changchun University, Changchun City, Jilin Province, China
Corresponding Author: He Zhang

ABSTRACT: *Agricultural pests cause substantial crop yield losses and remain a major constraint on stable grain production and sustainable agricultural development. Conventional field scouting and laboratory identification are often labor-intensive, time-consuming, subjective, and difficult to apply at large scales during the early stages of pest occurrence. In contrast, unmanned aerial vehicle (UAV) low-altitude remote sensing provides centimeter-level spatial resolution, flexible deployment, relatively low operating cost, and strong compatibility with multiple sensors. By integrating RGB, multispectral, hyperspectral, thermal infrared, and LiDAR data with vegetation-index inversion, machine learning, deep learning, and multi-source data fusion, UAV systems can identify pest-induced stress before visible symptoms become obvious, generate prescription maps, and support variable-rate pesticide application. This paper reviews the spectral and physiological mechanisms of pest stress, summarizes the characteristics of major UAV-borne sensors, discusses key data-processing and detection methods, and analyzes typical applications in rice, wheat, maize, cotton, fruit trees, and economic forests. It further proposes a monitoring-control closed loop and discusses existing challenges and future trends, including multimodal fusion, edge artificial intelligence, autonomous field scouting, time-series prediction, open benchmark datasets, and integrated space-air-ground monitoring systems.*

Date of Submission: 13-06-2026 Date of acceptance: 27-06-2026

I. INTRODUCTION

Global agricultural production suffers annual yield losses of approximately 10% to 40% due to pests and diseases, with economic losses exceeding USD 220 billion [1-2]. Traditional pest detection relies mainly on manual field scouting, visual inspection, or laboratory microscopic examination. These approaches require heavy labor input, provide poor timeliness, depend strongly on subjective judgment, and make early detection difficult at large spatial scales. Although satellite remote sensing can cover broad areas, its spatial and temporal resolution is often insufficient for field-level precision monitoring.

UAV low-altitude remote sensing has therefore become an important method for crop pest and disease monitoring at the field scale because it offers centimeter-level spatial resolution, flexible deployment, low cost, and the capacity to carry multiple sensors [4-5]. By mounting RGB, multispectral (MSI), hyperspectral (HSI), thermal infrared (TIR), and light detection and ranging (LiDAR) sensors, and by combining vegetation-index inversion with artificial intelligence algorithms, UAVs can identify pest stress before symptoms are visible to the naked eye. They can also generate pest-distribution prescription maps for precision variable-rate pesticide application, thereby reducing pesticide use and improving control efficiency.

II. SPECTRAL AND PHYSIOLOGICAL MECHANISMS OF AGRICULTURAL PEST STRESS

Pest feeding, including piercing-sucking, chewing, and boring damage, induces a series of physiological and biochemical changes in crops. These changes form the physical basis of remote-sensing detection.

First, chlorophyll degradation is a major response. When pests feed on mesophyll tissue and damage chloroplast structures, the content of chlorophyll a and chlorophyll b decreases. This process increases reflectance in visible bands, especially around the green band at 550 nm and the red band at 670 nm, while reducing reflectance in the near-infrared range from 760 to 1300 nm.

Second, leaf water content declines. Piercing-sucking pests such as aphids and leafhoppers extract phloem sap, reduce leaf water potential, and alter spectral responses in water-absorption bands such as 970 nm and 1450 nm.

Third, canopy structure and texture change. Pest damage can cause leaf curling, holes, yellowing, wilting, or defoliation, which reduces fractional vegetation cover (FVC) and leaf area index (LAI). In RGB images, these effects appear as abnormal color and texture patterns.

Fourth, canopy temperature may increase. Damage can weaken plant transpiration or alter stomatal conductance, causing a slight rise in canopy temperature that can be captured by thermal infrared sensors. These differences in spectral fingerprints provide the core basis for distinguishing healthy plants from pest-stressed plants using UAV remote sensing [6].

III. UAV-BORNE SENSOR TYPES AND CHARACTERISTICS IN PEST DETECTION

Table 1. UAV-borne sensor types and their characteristics in pest detection.

Sensor type	Band/parameter	Advantages for pest detection	Limitations
RGB camera	Red, green, and blue channels	Low cost; useful for extracting color features such as yellowing and browning, texture features such as holes and leaf curling, and plant height through photogrammetry; suitable for identifying obvious late-stage pest symptoms.	Unable to detect asymptomatic stress and strongly affected by illumination conditions.
Multispectral sensor (MSI)	Usually five bands, such as blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near infrared (842 nm).	Red-edge and near-infrared bands are sensitive to chlorophyll variation; NDVI, GNDVI, OSAVI, and related vegetation indices can be calculated to quantify pest severity; cost-effective and already commercialized, such as DJI P4 Multispectral.	The number of bands is limited, generally three to six, making it difficult to distinguish different stress types in detail.
Hyperspectral sensor (HSI)	Continuous narrow bands from 400 to 1000 nm or longer, with 2 to 10 nm spectral resolution and hundreds of bands.	Capable of capturing subtle shifts in spectral curves; continuous wavelet transform and sensitive-band selection can support early, even pre-symptomatic, pest detection and help distinguish pest stress from disease, drought, and waterlogging stress.	Large data volume, complex processing, expensive sensors, and strong dependence on atmospheric and illumination correction.
Thermal infrared sensor (TIR)	8 to 14 μm; obtains canopy temperature.	Detects canopy warming caused by stomatal closure or abnormal transpiration, which is useful for monitoring piercing-sucking pests.	Strongly affected by air temperature and wind speed, and its spatial resolution is usually lower than that of optical cameras.
LiDAR	Laser echoes used to obtain three-dimensional point clouds.	Retrieves plant height, canopy volume, and biomass; assists in identifying severe missing-plant or defoliation-type pest damage.	Cannot directly reflect spectral physiological information and is mainly used for multi-source fusion.

IV. KEY DATA-PROCESSING AND PEST DETECTION METHODS

4.1 Preprocessing and Radiometric Correction

UAV imagery is the core data source for pest detection, and its quality directly determines the accuracy of subsequent analysis. Therefore, systematic preprocessing and radiometric correction are required. In geometric correction, POS/GPS auxiliary data are used to correct spatial-position deviations accurately and to eliminate positional errors caused by flight attitude, terrain fluctuation, and related factors. This process ensures that image coordinates match the geographic space. In radiometric calibration, a standard reflectance panel is used to convert raw digital number (DN) values into surface reflectance, thereby reducing the interference of external factors such as illumination intensity and sensor characteristics. This step improves data consistency across different acquisition times and illumination conditions and provides a basis for comparing vegetation indices over time. Orthomosaic generation produces digital orthophoto maps (DOMs) and digital surface models (DSMs), which preserve geometric accuracy while providing terrain and height information. Together, these products establish a standardized three-dimensional field-data foundation for subsequent pest-distribution analysis.

4.2 Vegetation-Index Inversion

Vegetation indices amplify pest-induced changes in plant physiological parameters by combining multispectral information, making them key indicators for early pest detection [7-9]. The normalized difference vegetation index (NDVI), calculated from near-infrared (NIR) and red bands, directly reflects vegetation chlorophyll content. When pest damage causes leaf injury and chlorophyll degradation, NDVI decreases significantly, which makes it one of the most widely used pest-indication indices. The green normalized difference vegetation index (GNDVI) and enhanced vegetation index (EVI) introduce green or blue channels and are more sensitive to changes in plant nitrogen content and chlorophyll concentration, especially under mild pest damage or early stress. The normalized difference red-edge index (NDRE) focuses on the red-edge band, which responds sensitively to changes in plant cell structure and can detect spectral differences before obvious yellowing appears in the early stage of pest infestation. The photochemical reflectance index (PRI) indirectly reflects plant stress by monitoring the energy-allocation status of photosystem II and therefore provides a physiological basis for pest-damage assessment. For specific pests, researchers may also select exclusive sensitive bands to construct disease or pest spectral indices, such as SDI or PSI, to improve the specificity of pest identification.

4.3 Traditional Machine-Learning Methods

Traditional machine-learning methods combine manual feature engineering with classical algorithms and show stable recognition performance in small- and medium-sample scenarios [10]. During feature engineering, technicians extract multidimensional information from images, including reflectance values of spectral bands, vegetation indices, and texture features derived from the gray-level co-occurrence matrix (GLCM), such as contrast, entropy, and homogeneity, which describe morphological changes after leaf injury. Dimensionality-reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) are then used to remove redundant features and retain core discriminative information. At the classification and regression stage, support vector machines (SVMs), with strong small-sample classification capability, are often used for binary identification of pest presence or absence [11]. Ensemble-learning methods such as random forest (RF), gradient boosting decision trees (GBDT), and XGBoost use the collaborative decisions of multiple decision trees, can process high-dimensional features, and show strong resistance to overfitting [12-13]. These methods are suitable for graded prediction of pest severity. For example, Ren and colleagues fused RGB and multispectral images through Gram-Schmidt fusion and used a GBDT model to estimate cotton aphid severity quantitatively. Partial least squares regression (PLSR) is particularly effective for handling collinearity in spectral data and is commonly used to establish quantitative relationships between pest stress and spectral parameters [14].

4.4 Deep-Learning Methods

Deep-learning methods use convolutional neural networks (CNNs) to learn joint spatial-spectral features automatically, reducing dependence on manual feature engineering and providing strong performance in complex pest-identification scenarios [15-16]. In basic applications, CNNs and fully convolutional networks (FCNs) can directly take RGB or multispectral images as inputs and automatically extract local texture and global spectral features through multiple convolutional layers. Encoder-decoder architectures such as U-Net and SegNet are effective for pixel-level segmentation of pest-damaged areas and can delineate the spatial distribution of damaged leaves [17]. In improved architectures, the residual connections of ResNet address degradation during deep-network training, EfficientNet balances accuracy and efficiency through compound scaling, and YOLO-series object-detection models can rapidly locate individual pests or damaged patches on single plants [18-20]. Transformer-based models use self-attention mechanisms to capture long-distance dependencies in large farmland scenes and are therefore suitable for wide-area pest monitoring [21].

For practical problems such as scarce labeled samples and weak cross-field generalization, multitask learning and transfer learning have become important technical routes. Multitask learning shares feature-extraction layers to complete pest identification, severity classification, and related tasks simultaneously, thereby improving model utilization. Transfer learning adapts models pretrained on large general datasets to specific crop-pest detection tasks and greatly reduces dependence on local labeled samples. Studies show that CNN-based pest-identification schemes combined with multispectral data can reach accuracies of 90% to 95% or higher, and they are especially advantageous in hidden pest infestation and compound-stress scenarios compared with traditional methods.

4.5 Multi-Source Data Fusion Strategies

In precision detection of agricultural pests and diseases, a single data source is often insufficient for handling the complexity of field environments. Multi-source data fusion has therefore become a core strategy for improving detection accuracy and reliability [22]. It supports pest detection through a hierarchical fusion path that includes data-level fusion, feature-level fusion, decision-level fusion, and multimodal collaborative enhancement.

Data-level fusion forms the foundation of the fusion system by directly connecting and integrating raw data. In practice, accurate image-registration techniques are first used to spatially align sensor data from different sources and dimensions, eliminating coordinate deviations and scale differences and ensuring spatial consistency. Registered multisource image bands are then directly stacked to construct a fusion dataset that contains rich original information. This approach preserves original data characteristics to the greatest extent and avoids information loss during preprocessing. It provides comprehensive data support for subsequent pest identification and is especially useful for preliminary screening scenarios that require high data completeness and the capture of subtle spectral changes caused by pests.

Feature-level fusion is the core stage of multisource fusion and emphasizes targeted extraction and integrated representation of key features from different modalities. For spectral, texture, and height data, corresponding algorithms are used to extract the most relevant features. Spectral features capture pest-induced changes in vegetation physiology, texture features reflect morphological differences after leaf injury, and height features derived from LiDAR data reveal subtle changes in plant structure. After extraction, these multidimensional features are concatenated into representative feature vectors and input into classifiers for training and recognition. By focusing on core information and filtering redundant content, feature-level fusion improves the precision and discriminative power of feature expression and enhances the model's ability to capture pest characteristics under complex backgrounds.

Decision-level fusion serves as the top-level decision stage of the fusion system. It uses independent interpretation models for different data modalities and then integrates their outputs. Each modality produces an independent pest-identification result according to its own features. A weighted-voting mechanism then considers the reliability, applicable scenario, and recognition accuracy of each modality and assigns different weights to the corresponding decisions. The final result is generated through integrated decision making. This approach fully uses the advantages of each modality and avoids the bias of relying on a single modality. Even when one modality is affected by environmental interference, other modalities can compensate, thereby improving robustness and accuracy in highly complex field environments.

Through data-level, feature-level, and decision-level fusion, multisource strategies create a complete system of complementary advantages and coordinated decision making. In complex field scenes, changes in illumination, vegetation occlusion, soil-background interference, and crop lodging can seriously disrupt pest detection. Multimodal fusion uses spectral data to capture physiological changes, texture data to identify morphological features, and height data to exclude structural disturbances. Cross-validation and complementarity among these dimensions help resist environmental interference and improve detection robustness. Whether the target is concealed leaf-mining pests or compound stress involving pests, diseases, and drought, multisource fusion provides comprehensive information support and enables reliable identification, thereby strengthening the technical basis for efficient pest control.

V. TYPICAL APPLICATIONS IN CROP PEST DETECTION

UAV remote-sensing technology has developed differentiated application paths in the precision prevention and control of pests and diseases across different crops. In rice, for pests such as the rice leaf folder and rice planthopper, hyperspectral UAVs can capture distinctive spectral features, including increased reflectance from 620 to 710 nm and decreased reflectance from 720 to 760 nm in damaged leaves. XGBoost models can then be used to construct pest heat maps for variable-rate pesticide application. The combination of multispectral NDVI and NDRE can accurately classify pest severity, especially during the jointing-to-heading stage, which is an optimal monitoring window for improving early identification.

In wheat fields, aphid feeding causes flag-leaf yellowing and inhibits grain filling. The red-edge band of UAV multispectral imagery is highly sensitive to early stress. When combined with U-Net segmentation and spectral-spatial feature fusion, high-accuracy detection of stripe rust can be achieved, while thermal infrared information assists in identifying canopy warming caused by severe aphid damage. This combination forms a multidimensional diagnostic system [3]. In maize fields, twelve sensitive bands selected from hyperspectral data can be used to establish monitoring models for northern corn leaf blight and borer damage, with R^2 values greater than 0.8. The fusion of multispectral and thermal infrared data helps distinguish disease-development stages, while LiDAR-based plant-height estimation can reduce the interference caused by lodging and improve recognition of compound disease and pest stress.

In cotton-growing areas, RGB and multispectral image fusion combined with GBDT modeling reveals a significant negative correlation between cotton aphid damage indices and vegetation indices and enables spatial visualization of aphid occurrence patches. For fruit trees and economic forests, multispectral UAV monitoring of olive verticillium wilt has shown early abnormalities in the green band [23]. LiDAR-hyperspectral fusion can accurately identify infection stages of pine wood nematode disease. Because orchard canopies are spatially discrete, single-tree marking and tree-by-tree analysis provide a refined solution for pest and disease prevention in woody plants.

VI. CONSTRUCTION OF A MONITORING-CONTROL CLOSED LOOP

The core value of UAV pest detection lies in connecting the full process of monitoring, diagnosis, prescription generation, and pesticide application, thereby building a closed-loop system from precise sensing to efficient control [4-5,22]. At the beginning of this loop, multispectral or hyperspectral UAVs collect field images along preset routes and establish the data foundation for subsequent decision making. In the AI interpretation stage, deep-learning models conduct in-depth analysis of the imagery and rapidly output gridded pest-distribution maps, transforming raw data into diagnostic results. Based on the diagnosis, the system divides pest severity into mild, moderate, and severe grades and generates variable-rate spraying prescription maps that specify application rates in L/ha or mL/plant.

Plant-protection UAVs then read the prescription maps and conduct differentiated spraying according to actual need. They increase application in high-incidence areas and reduce or avoid application in low-incidence areas. While maintaining control effectiveness, this strategy can reduce pesticide use by 30% to 40% and reduce control costs by approximately 30%. At the end of the closed loop, UAVs revisit the field after pesticide application to evaluate control effectiveness through follow-up scouting. This step verifies the implementation effect and provides evidence for optimizing subsequent control strategies. The result is a linked and dynamically updated full-chain system that enables UAV pest detection to move from precise detection to efficient field control.

VII. EXISTING CHALLENGES

Current agricultural pest and disease monitoring and early-warning systems still face several practical bottlenecks. In early detection, the spectral signals of extremely mild or leaf-mining pests are very weak and are easily masked by soil background and environmental noise, making accurate recognition and advance warning difficult. In terms of model generalization, many existing models are trained on data from specific cultivars, growth stages, and regions, and their performance declines significantly when applied across domains. The absence of public standardized datasets and unified benchmarks further limits algorithm generality and iterative improvement [3,22].

The promotion of hyperspectral technology is also constrained by the high cost of sensors and the pressure of processing massive data volumes. Real-time field analysis still depends heavily on the maturity and wider adoption of edge-computing technologies, and the threshold for practical deployment remains high. Flight-operation efficiency is another limitation. A single UAV can cover only several hundred mu, and large contiguous farmland requires multi-UAV cooperation or coordination with satellite remote sensing to achieve full-area coverage. In addition, the spectral characteristics of pests, diseases, and drought stress are often highly similar. Relying on a single modality alone cannot support accurate discrimination. Reliable identification therefore requires deep multisource information fusion together with ground verification. These challenges have become key constraints on improving the effectiveness of monitoring systems and require systematic solutions.

VIII. DEVELOPMENT TRENDS AND PROSPECTS

From the perspective of future development, the deep integration of multisource heterogeneous sensor fusion and vision-language models (VLMs) is expected to become a core pathway for improving diagnostic accuracy in complex scenes. The strong cross-modal understanding ability of large models can create new possibilities for precise identification [24]. Edge AI and autonomous field scouting will also become more widely adopted. With the real-time inference capability of onboard neural processing units and the support of RTK/BeiDou positioning, UAVs can conduct fully automatic, scheduled, and fixed-point patrols, pushing field operations toward greater intelligence and autonomy.

Time-series monitoring and prediction will overcome the limitations of one-time detection by integrating meteorological data, phenological information, and historical pest databases to build spatiotemporal diffusion models. This will support the transition from passive detection to active early warning and strengthen the first line of pest and disease prevention. At the same time, standardization and open benchmark construction are essential. The improvement and release of public UAV remote-sensing datasets for pest detection will provide a unified platform for fair algorithm comparison and accelerate the transformation of research outcomes into practical applications.

In the future, an integrated space-air-ground monitoring system will become the mainstream architecture. UAVs, with their flexibility, can fill the scale gap between satellite-based macro monitoring and ground-based micro observation. By linking these three levels into an integrated monitoring and early-warning closed loop, UAV technology can comprehensively support agricultural pest and disease control, strengthen the scientific and technological foundation for high-quality agricultural development, and outline a new model of precision pest management in smart agriculture.

REFERENCES

[1] SAVARY S, WILLOCQUET L, PETHYBRIDGE S J, et al. The global burden of pathogens and pests on major food crops[J]. Nature Ecology & Evolution, 2019, 3(3): 430-439.
[2] OERKE E C. Crop losses to pests[J]. The Journal of Agricultural Science, 2006, 144(1): 31-43.
[3] ZHANG J, HUANG Y, PU R, et al. Monitoring plant diseases and pests through remote sensing technology: A review[J]. Computers and Electronics in Agriculture, 2019, 165: 104943.
[4] MAES W H, STEPPE K. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture[J]. Trends in Plant Science, 2019, 24(2): 152-164.
[5] HUNT E R, DAUGHTRY C S T. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture?[J]. International Journal of Remote Sensing, 2018, 39(15-16): 5345-5376.
[6] MAHLEIN A K. Plant disease detection by imaging sensors—Parallels and specific demands for precision agriculture and plant phenotyping[J]. Plant Disease, 2016, 100(2): 241-251.
[7] TUCKER C J. Red and photographic infrared linear combinations for monitoring vegetation[J]. Remote Sensing of Environment, 1979, 8(2): 127-150.
[8] RONDEAUX G, STEVEN M, BARET F. Optimization of soil-adjusted vegetation indices[J]. Remote Sensing of Environment, 1996, 55(2): 95-107.
[9] GAMON J A, PEÑUELAS J, FIELD C B. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency[J]. Remote Sensing of Environment, 1992, 41(1): 35-44.
[10] SINGH A, GANAPATHYSUBRAMANIAN B, SINGH A K, et al. Machine learning for high-throughput stress phenotyping in plants[J]. Trends in Plant Science, 2016, 21(2): 110-124.
[11] CORTES C, VAPNIK V. Support-vector networks[J]. Machine Learning, 1995, 20(3): 273-297.
[12] BREIMAN L. Random forests[J]. Machine Learning, 2001, 45(1): 5-32.
[13] CHEN T, GUESTRIN C. XGBoost: A scalable tree boosting system[C]//Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York: ACM, 2016: 785-794.
[14] WOLD S, SJÖSTRÖM M, ERIKSSON L. PLS-regression: A basic tool of chemometrics[J]. Chemometrics and Intelligent Laboratory Systems, 2001, 58(2): 109-130.
[15] LECUN Y, BENGIO Y, HINTON G. Deep learning[J]. Nature, 2015, 521(7553): 436-444.
[16] KAMILARIS A, PRENAFETA-BOLDÚ F X. Deep learning in agriculture: A survey[J]. Computers and Electronics in Agriculture, 2018, 147: 70-90.
[17] RONNEBERGER O, FISCHER P, BROX T. U-Net: Convolutional networks for biomedical image segmentation[C]//Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015. Cham: Springer, 2015: 234-241.
[18] HE K, ZHANG X, REN S, et al. Deep residual learning for image recognition[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Las Vegas: IEEE, 2016: 770-778.
[19] TAN M, LE Q V. EfficientNet: Rethinking model scaling for convolutional neural networks[C]//Proceedings of the 36th International Conference on Machine Learning. 2019: 6105-6114.
[20] REDMON J, DIVVALA S, GIRSHICK R, et al. You Only Look Once: Unified, real-time object detection[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Las Vegas: IEEE, 2016: 779-788.
[21] VASWANI A, SHAZEER N, PARMAR N, et al. Attention is all you need[C]//Advances in Neural Information Processing Systems. 2017, 30: 5998-6008.
[22] WEISS M, JACOB F, DUVEILLER G. Remote sensing for agricultural applications: A meta-review[J]. Remote Sensing of Environment, 2020, 236: 111402.
[23] CALDERÓN R, NAVAS-CORTÉS J A, LUCENA C, et al. High-resolution airborne hyperspectral and thermal imagery for early detection of Verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices[J]. Remote Sensing of Environment, 2013, 139: 231-245.
[24] RADFORD A, KIM J W, HALLACY C, et al. Learning transferable visual models from natural language supervision[C]//Proceedings of the 38th International Conference on Machine Learning. 2021: 8748-8763.