

Review

Research Progress on Remote Sensing Monitoring of Diseases and Insect Pests of Major Grain Crops

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Abstract

As an important factor affecting the yield and quality of grain crops and threatening grain security, traditional pest and disease monitoring can no longer meet the needs of accurate and efficient agricultural production. The development of remote sensing technology provides a new monitoring method, which is specific, accurate and efficient, and provides real-time, rapid and non-destructive spectral data information for the identification of the occurrence and severity of pests and diseases and can realize large-scale monitoring of grain crop pests and diseases. In this paper, through the statistics and analysis of the published literature on remote sensing monitoring of grain crop diseases and pests, the research hotspots and directions of remote sensing monitoring of grain crop diseases and pests are clarified. Based on this foundation, this paper systematically elaborates the mechanism underlying remote sensing-based monitoring and prediction of diseases and insect pests in grain crops. It reviews various remote sensing monitoring approaches for such diseases and pests by leveraging multi-source remote sensing data. Furthermore, it summarizes methodologies for constructing monitoring and prediction models for grain crop diseases and insect pests. Finally, the paper discusses current challenges and future development trends in this field.

Keywords: grain crops; pests and diseases; remote sensing monitoring models; multi-source remote sensing data



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1. Introduction

Agriculture serves as a cornerstone for the stable development of the national economy. From 2004 to 2025, Central Document No. 1 has consistently prioritized agricultural issues, with continued emphasis on ensuring stable grain production and supply [1]. In crop production, pests and diseases occur intermittently and vary widely in type, often leading to large-scale and explosive outbreaks that severely impact crop yields and quality, resulting in significant losses to China's agricultural sector. The severity of pests and diseases of grain crops lies in the fact that they occur on an ever-expanding scale and are characterized by large-scale and explosive disasters. The National Agro-Technical Extension and Service Center convened experts from plant

protection institutions and research and teaching units to conduct a comprehensive analysis and discussion of the nationwide trends in major crop diseases and pests for 2025. Based on a comprehensive analysis of factors including pest and disease inoculum levels, cropping systems, crop distribution, and climatic conditions, it is projected that 23 major pests and diseases will affect key grain crops—such as wheat, rice, and corn—as well as oilseed and vegetable crops in 2025. The estimated nationwide affected area is 167 million hm^2 , representing a 6.2% increase compared to 2024. It is projected that the area affected by the “four diseases and one pest” (Wheat scab, Wheat Stripe Rust, wheat sharp eyespot, Wheat crown rot and wheat aphid) of wheat will reach 40.4 million hm^2 , accounting for 64.2% of the total area impacted by wheat diseases and pests, representing an 8.2% increase compared to 2024. It is projected that the area affected by the “three pests and two diseases” (Rice blast, Rice sheath blight, *Chilo suppressalis*, *Nilaparvata lugens* (Stål), and *Cnaphalocrocis medinalis* Guenee) in rice will reach 74.6 million hm^2 , accounting for 86.8% of the total area impacted by rice pests and diseases, representing a 4.7% increase compared to 2024. Soybean root rot is expected to affect 1 million hm^2 of cropland nationwide, with moderate incidence in Heilongjiang Province and more severe outbreaks in certain low-lying and flood-prone areas [2]. These pests and diseases have severely impacted grain production and quality, resulting in substantial agricultural losses and emerging as an urgent issue that requires immediate attention in current agricultural production.

Chemical control can partially mitigate the impact of pests and diseases on crops; however, unscientific use of pesticides may easily induce pathogen resistance, often leading to issues such as frequent applications and reduced efficacy, while simultaneously causing pesticide residues, secondary pest outbreaks, and environmental pollution [3–6]. Therefore, the key and foundation of precise control lies in promptly identifying the location, extent, and severity of pest and disease outbreaks. Compared with remote sensing-based monitoring of pests and diseases, traditional crop pest and disease monitoring methods primarily rely on manual surveys, which are associated with significant workloads, high subjectivity, and poor timeliness. They are insufficient to meet the requirements for large-scale and precise monitoring of crop pests and diseases. In addition, chemical control is incapable of supporting large-scale precise monitoring and early warning, whereas remote sensing technology enables large-scale, rapid, and non-destructive monitoring of the occurrence, development, and spatial distribution of pests and diseases, thereby providing a scientific basis for precise control.

Currently, early warning and identification models for crop pests and diseases are primarily based on historical meteorological data and observed disease incidence [7,8]. Although they can provide macroscopic trends of pest and disease occurrence, they are unable to meet the requirements for precise and efficient control of grain crop pests and diseases. Correspondingly, amid the accelerated modernization of agriculture, 3S technology (Geographic Information System (GIS), Global Positioning System (GPS), and Remote Sensing technology (RS)) and multispectral and hyperspectral remote sensing monitoring technologies have been widely applied to the monitoring of pests and diseases in grain crops [9]. Remote sensing technology analyzes the conditions of ground objects by capturing their reflected or emitted radiation. When crops are subjected to biological stress, their physiological and biochemical parameters, as well as external morphology change, leading to alterations in their reflectance across different spectral bands, thereby causing differences in the spectral information detected by remote sensing [10]. Remote sensing monitoring technology offers advantages such as non-contact measurement, low cost, and extensive coverage, enabling accurate and rapid identification of crop disease and pest occurrences, and has become a key approach for crop pest and disease monitoring [11,12]. This paper

summarizes the existing challenges and future development trends in current research on disease and pest monitoring and prediction for grain crops, and systematically reviews the mechanisms, methodologies, and model construction approaches in remote sensing-based monitoring and prediction of diseases and pests in the major grain crops, as well as recent research progress in this field.

2. Mechanism of Remote Sensing-Based Monitoring and Forecasting of Pests and Diseases in Grain Crops

Under disease stress, crops exhibit changes in external characteristics such as morphology, color, and texture. The crop's defense system mitigates damage, resulting in alterations in physiological and biochemical parameters. These changes can be detected using various spectroscopic techniques based on distinct physical principles. To detect crop diseases, researchers have employed various spectroscopic techniques, among which the visible and infrared spectral bands are commonly used for the identification of crop pests and diseases.

Under the influence of chlorophyll, healthy leaves exhibit higher absorption and lower reflectance in the visible spectral region. Due to the internal cellular structure of leaves, the near-infrared spectral region exhibits higher reflectance [13,14]. For example, the larvae of the fall armyworm feed on the mesophyll, damaging both the epidermis and mesophyll tissues of rice leaves, impairing photosynthesis and ultimately reducing yield, thereby causing significant harm. During this process, the spectral reflectance exhibits an overall increasing trend in the near-infrared spectral region [15]. Feng et al. investigated the identification of rice sheath blight, rice blast, and bacterial blight using three types of spectra: visible/near-infrared hyperspectral, mid-infrared, and laser-induced fluorescence spectra, and found that the classification model based on visible/near-infrared hyperspectral data achieved 100% accuracy [16]. The above research demonstrated that visible light and near-infrared hyperspectral imaging can effectively differentiate various rice pests and diseases and enable reliable monitoring of their occurrence.

Healthy wheat leaves display characteristic spectral signatures in the visible-to-near-infrared (VNIR) range, marked by low reflectance at the “green peak,” a sharp rise across the “red edge” region, and high reflectance in the “near-infrared plateau.” Upon infestation by aphids or infection by stripe rust or powdery mildew, chlorophyll degradation increases reflectance in the green-to-red spectrum, while disruption of mesophyll cell structure leads to a pronounced reduction in near-infrared reflectance—evident as a blue shift in the “red edge” and a loss of NIR signal. Leveraging this physiological–spectral response mechanism, drone-based hyperspectral monitoring using a 400–900 nm sensor system in 2023 revealed that fields affected by aphids during the heading stage exhibited an average reflectance decline of 5–7 percentage points in the 680–750 nm and 970 nm bands; when integrated with the XGBoost algorithm, this enabled early detection with 92% accuracy [17]. In parallel, a winter wheat stripe rust experiment conducted the same year showed that diseased plants' near-infrared reflectance dropped from 25% under healthy conditions to 20%, and a random forest model trained on these spectral differences achieved a prediction coefficient of determination (R^2) of 0.84 for a disease severity index of level three [18]. Thus, during the jointing to grain-filling stages, integrating airborne or satellite-borne VNIR hyperspectral data with meteorological and phenological information allows for the development of a “spectral response–pest and disease threshold” association model, supporting short-term 3–7-day forecasting and variable-rate application decisions for wheat pests and diseases at the county level.

Xu Jing acquired spectral data in the visible and near-infrared ranges through in vitro inoculation, applied the mixed distance method to identify 465.1 nm, 550.7 nm, and 681.4 nm as characteristic wavelengths, and developed a BP neural network model that

achieved an identification accuracy of 97.5% [19]. Similarly, Wang et al. found that in the 600–800 nm spectral range, the reflectance of corn leaves infected with large spot disease exhibited a distinct peak with a center reaching an extreme value [20]. Richard analyzed maize lethal necrosis (MLN) using sensitive spectral bands. The normalized difference red edge index (NDRE) was highly sensitive to MLN detection and demonstrated an earlier capacity to identify MLN-induced crop stress compared to the normalized difference vegetation index (NDVI) and the green normalized difference vegetation index (GNDVI) [21] (Table 1). The above research demonstrates that hyperspectral technology has significant potential for monitoring corn pests and diseases, with improved detection accuracy achieved through spectral data transformation.

Table 1. Spectral indices of crop diseases and pests' quantitative analysis.

Name	Formula
NDRE	$(\text{NIR} - \text{REG})/(\text{NIR} + \text{REG})$
NDVI	$(\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})$
GNDVI	$(\text{NIR} - \text{GREEN})/(\text{NIR} + \text{GREEN})$

Note: NIR represents near-infrared band reflectivity, GREEN represents green band reflectivity, REG stands for red-edge band reflectivity, and RED stands for red light band reflectivity.

When soybeans are infected by diseases, their growth and development are severely impaired; when attacked by pests, the insects feed on and extract sap from the plants, damaging their structural integrity and ultimately reducing crop yield. Pest and disease monitoring and prediction in soybeans are primarily based on normalized vegetation indices [22]. In the visible light region, Gazala et al. observed an increase in canopy spectral reflectance, followed by a decrease in the near-infrared region, following soybean yellowing disease infection; reflectance sensitivity analysis revealed significant responses at wavelengths of 642 nm, 686 nm, and 750 nm to yellow rot infection [23]. The above research confirmed that when soybeans are infected by diseases or infested by pests, canopy spectral reflectance undergoes changes, and models constructed using sensitive spectral bands can be effectively utilized for monitoring and early warning of such hazards [24].

It can be concluded that different crop diseases and pests interact with their hosts in distinct ways, inducing varied physiological and biochemical responses in plants—such as chlorophyll degradation, cell structure damage, water stress, or the accumulation of specific defensive compounds (e.g., phenolics) [25]. These responses, in turn, alter the optical properties of plant tissues, causing diagnostic spectral changes in specific wavelength ranges (e.g., the red-edge region related to chlorophyll, and near-infrared associated with cell structure) [24,26]. These specific symptom manifestations form the foundation for the identification and monitoring of crop diseases and pests using hyperspectral technology.

3. Multisource Remote Sensing for Early Detection and Forecasting of Cereal Crop Pests and Diseases

In recent years, advances in remote sensing technology have led to increasingly diverse remote sensing monitoring platforms. Currently, mainstream monitoring platforms primarily include ground-based remote sensing [27–29], unmanned aerial vehicle (UAV) remote sensing [30–32], and satellite remote sensing systems [33–35]. These platforms play distinct roles in monitoring pests and diseases in grain crops. To systematically summarize and compare the key characteristics of representative studies employing these platforms, Table 1 consolidates essential information, including target crops, pests/diseases, data sources, and analytical methods (Table 2).

Table 2. Summary of research on monitoring pests and diseases in grain crops using multi-source remote sensing platforms.

Crop	Pathogen/Pest/Reference	Data Source	Core Method/Feature
Ground-based Remote Sensing Platforms			
Rice	Rice leaf roller [27] Rice blast [36] Diseases [37]	Imaging spectrometer Ground & UAV hyperspectral Portable multispectral/RGB camera	Spectral reflectance Data fusion and modeling Integration of SPAD values
Wheat	Fusarium head blight [28] Greenbug [38]	Hyperspectral imager Ground spectroradiometer	Chlorophyll fluorescence Narrow-band remote sensing
Maize	Curvularia leaf spot [39] Gray leaf spot, NCLB, Southern rust [29]	Hyperspectral imaging Field spectrometer PSR-3500	Characteristic band extraction & classification Normalized ratio method
Soybean	Mosaic virus [40] Gray leaf spot, bacterial leaf spot [41]	Hyperspectral imager Hyperspectral curve	CNN Principal Component Analysis, spectral indices
UAV Remote Sensing Platforms			
Rice	Bacterial leaf streak [30] Diseases [42]	UAV hyperspectral UAV spectral reflectance	SVM Segmented spectral index model
Wheat	Fusarium head blight [31] Stem rust [17] Northern corn leaf blight [43]	UAV hyperspectral UAV hyperspectral UAV hyperspectral	Feature fusion & Random Forest Random Forest classification Sensitive band screening and modeling
Maize	Pests and diseases [44] Northern corn leaf blight, Curvularia leaf spot [32]	UAV RGB image UAV multispectral & thermal infrared	Machine learning Multi-source data fusion and monitoring model
Satellite Remote Sensing Platforms			
Crop	Pests and diseases [33] Growth monitoring [45]	WorldView-2, Landsat-8 GF-2	Vegetation index & FLDA model Broadband vegetation indices
Winter wheat	Powdery mildew & aphids [34] Stripe rust [35]	Dual-temporal Landsat-8 Sentinel-2	SMOTE-BPNN method REDSI
Maize	Sheath blight & brown planthopper [46] Red spider mite, NCLB, Armyworm [47] Armyworm [21]	SPOT satellite imagery High-resolution satellite imagery Multi-temporal hyperspectral satellite data	RVI, SDI14, SDI indices Statistical methods with meteorological data Plant-canopy indices & dynamic model

3.1. Ground-Based Remote Sensing Platforms

Using ground-based remote sensing observation technology, spectral information from crop leaves or canopies can be obtained [48]. This technology demonstrates relatively high accuracy in identifying crop pests and diseases in experimental plots. Tian et al. used an imaging spectrometer to analyze spectral reflectance and vegetation index differences between pest-infested and healthy rice leaves, thereby obtaining spectral signatures of rice leaf infection by rice leaf roller pests, and established a model to assess the severity of pest damage [27]. Zhu integrated ground-based and UAV-borne hyperspectral data to develop a rice blast disease detection model, achieving an accuracy exceeding 96% [36]. Su collected rice canopy data using a portable multispectral imager and an RGB camera, integrating SPAD values to develop a monitoring model that achieved high accuracy during critical growth stages, particularly the flowering period, and showed strong potential for rapid field diagnosis [37]. Critically, the true potential of hyperspectral technology extends beyond accurate identification to enabling pre-symptomatic detection of crop stress, offering a decisive advantage for early intervention. Ghulam Mustafa used a hyperspectral imager to obtain hyperspectral data of wheat leaves [28]. Through a stepwise floating feature selection method based on machine learning, he selected the reciprocal of the reflectance at 700 nanometers and 2 to 3 chlorophyll fluorescence features. These features enabled the detection of Fusarium head blight in wheat spikes at the symptom-free and early stages with accuracies of 87% and 95%, respectively [28]. This achievement underscores those hyperspectral measurements can detect subtle physiological disruptions—such as changes in photosynthetic efficiency reflected in chlorophyll fluorescence features—well before

visible symptoms manifest. This capability aligns with the principle of chlorophyll fluorescence imaging for early stress detection, thereby positioning ground-based hyperspectral remote sensing as a vital tool for effective early warning systems [26]. Mirik utilized spectral reflectance data acquired by a ground-based spectroradiometer to monitor greenbug infestations, achieving R^2 values ranging from 0.62 to 0.85 [38]. Narrow-band remote sensing demonstrated high accuracy in mapping both greenbug population density and wheat physiological stress under field and greenhouse conditions [38]. Xu Jing's team systematically classified corn leaf diseases, including *Curvularia* leaf spot, by extracting characteristic spectral bands through hyperspectral imaging technology and developing a classification model [39]. Shen Y. employed a PSR-3500 field spectrometer (350–2500 nm) to acquire hyperspectral data for three corn leaf diseases—gray leaf spot, northern leaf blight, and southern rust—across varying disease severity levels [29]. A standardized ratio method was developed to mitigate the effects of varietal and growth stage differences, achieving an overall accuracy (OA) of 95.06% in disease type identification under severe infection conditions [29]. Gui et al. established a convolutional neural network (CNN) model for detecting soybean mosaic disease using spectral information collected by a hyperspectral imager from soybean leaves [40]. The training set achieved an accuracy of over 92%, laying the foundation for the early and rapid detection of soybean mosaic disease [40]. Liu et al. analyzed the spectral characteristics of soybean leaf diseases based on hyperspectral curves, extracted disease-related effective information using principal component analysis and spectral indices, and established two disease classification models for gray spot and bacterial spot, proposing that both visible and near-infrared spectral regions can be used as monitoring bands [41].

Ground-based remote sensing monitoring platforms have demonstrated significant advantages in crop pest and disease monitoring, including large coverage, high timeliness, accurate identification, and low cost. Combined with hyperspectral technology and artificial intelligence, early warning and dynamic monitoring of pests and diseases can be achieved, with prediction accuracy exceeding 90%. Ground-based remote sensing platforms provide benefits for high-precision monitoring of pests and diseases [27–29]; however, their practical deployment in the field is limited by environmental sensitivity and insufficient capability for micro-level detection. These systems require stable operating conditions and are susceptible to interference from weather and terrain, which can lead to inconsistent data quality [29,38]. Additionally, they often fail to reliably detect subtle early indicators of pest or disease presence within complex field settings [28,36]. In addition, existing studies are primarily based on laboratory or small-scale field trials, and the models exhibit insufficient generalization, making it difficult to adapt to the complex and variable patterns of disease and pest occurrence in large-scale field conditions, such as mixed infections of multiple diseases, variations between crop varieties, and interference from soil background. Therefore, there is an urgent need for a more flexible and efficient monitoring approach to address these limitations. The UAV remote sensing monitoring platform, with its strong mobility, high cost-effectiveness, low susceptibility to weather conditions, and high spatiotemporal resolution, has become an important supplementary tool for field-based pest and disease monitoring. The multispectral camera, hyperspectral imager, and LiDAR sensors it carries can rapidly acquire spectral information from crops. When combined with intelligent algorithms, they further enhance the diversity and accuracy of monitoring.

3.2. UAV Remote Sensing Platforms

Based on the observation capabilities of the UAV remote sensing monitoring platform, spectral monitoring of grain crops at the field scale enables high-precision quantitative monitoring of crop pests and diseases, offering advantages such as high spatial resolution, low cost, and operational flexibility.

In recent years, the UAV remote sensing monitoring platform has achieved significant progress in the field of rice disease monitoring. Ding et al. employed UAV-based hyperspectral monitoring to detect rice bacterial stripe disease, established a support vector machine classification model, and utilized both characteristic bands and full-spectrum bands to assess disease damage, achieving a model accuracy of 93.48% [30]. Liu et al. utilized the UAV remote sensing monitoring platform to acquire rice canopy spectral reflectance at the panicle stage and developed a two-segment and three-segment spectral index estimation model, achieving a maximum R^2 of 0.81, demonstrating its potential for application [42]. In summary, the integration of drones equipped with hyperspectral sensors and machine learning algorithms has enabled precise identification and severity grading of rice diseases, with some models achieving accuracies exceeding 93%.

In recent years, UAV remote sensing platforms have made significant advances in monitoring wheat pests and diseases, achieving a full-process technological breakthrough in “identification–grading”. Zhang et al. demonstrated that a model integrating UAV-based hyperspectral bands, texture, and color features—optimized via random forest selection—achieved 85% detection accuracy for *Fusarium* head blight in wheat under field conditions, offering an effective pathway for precision disease management [31]. UAV-based hyperspectral imaging combined with random forest successfully classified wheat stem rust in 960 plots into four severity levels, achieving an overall classification accuracy of 85%, and 88% accuracy for the binary distinction between mild and disease-free conditions. The approach enables early detection of low-severity infections and supports resistance breeding programs [17]. These studies collectively demonstrate that UAV platforms have established a comprehensive technical framework encompassing early detection, severity grading, and variable control guidance for wheat pests and diseases, thereby laying a robust foundation for multi-scale and multi-dimensional monitoring systems.

Existing research has made significant progress in applying UAV remote sensing monitoring platforms to corn disease monitoring, with related technologies enabling full-process monitoring from disease identification to severity assessment. Based on the UAV hyperspectral imaging technology platform, Liang et al. investigated the spectral response of corn leaves under northern corn leaf blight (NCLB) infection, screened out 12 sensitive bands, and achieved R^2 values above 0.8 across all eight groups in 13 established monitoring models for corn canopy large spot disease. In the actual measurement of large spot disease in the canopy, the correlation with the disease index value was highly significant [43]. Feng Jiedong used a small drone to collect RGB images and, based on machine learning, constructed an accurate method for extracting information on the location and extent of corn pests and diseases [44]. Jia Xiao utilized drone-based multispectral and thermal infrared imagery to identify and differentiate the developmental stages of NCLB and corn *Curvularia* leaf spot following infection, constructed monitoring models, and assessed disease severity. The R^2 of monitoring models for different disease grades was above 0.76, demonstrating the advantage of multi-source data fusion in distinguishing complex diseases [32]. These studies not only confirmed the applicability of drone platforms in corn disease monitoring but also laid the technical foundation for establishing a multi-scale and multi-dimensional pest and disease monitoring system.

In conclusion, the UAV remote sensing monitoring platform has been widely applied at the field scale with high accuracy. However, the technology still has notable limitations in practical application: the monitoring range of drones is limited, and a single operation can cover only several hundred acres, which makes it difficult to meet the demand for large-scale disease monitoring. The data collection is constrained by flight endurance and weather conditions, making it difficult to achieve high-frequency, continuous observation over large areas. In addition, standardizing drone data across different regions remains challenging, leading to reduced comparability of monitoring results between regions. These shortcomings highlight the urgent need for large-scale, all-weather, and standardized remote sensing monitoring methods; satellite remote sensing platforms, with their wide coverage, stable revisit cycles, and unified data standards, can effectively address the limitations of UAV platforms. In particular, the emergence of a new generation of high-resolution multi-spectral satellites and satellite constellations dedicated to agricultural monitoring has enabled satellite remote sensing to demonstrate significant value in large-scale crop disease and pest monitoring, providing key technical support for the development of an integrated intelligent monitoring system for agricultural diseases based on the “space-air-ground” framework.

3.3. Satellite Remote Sensing Platforms

The satellite remote sensing monitoring platform, with its wide observation range and continuous monitoring capability, is well suited for regional-scale remote sensing monitoring and identification of pests and diseases in grain crops. Yuan et al. utilized WorldView-2 and Landsat-8 satellite data in combination with the vegetation index-based FLDA model to identify five key features, including the crop growth index, for crop pest and disease forecasting [33]. Tang Qian used GF-2 satellite data to calculate broadband vegetation indices and construct high-accuracy inversion models for SPAD, leaf curl rate, and LAI, with R^2 values exceeding 0.7, thereby verifying the application potential of domestic high-resolution satellites in crop growth monitoring [45]. Ma et al. utilized dual-temporal Landsat-8 images, integrated crop growth and environmental parameters, and applied the SMOTE-BPNN method to achieve accurate discrimination of co-occurring powdery mildew and aphid infestations in winter wheat at the regional scale [34]. Zheng developed the Sentinel-2 red-edge disease stress index (REDSI), enabling rapid discrimination of healthy, mild, and severe stripe rust infections in winter wheat at the regional scale with an overall accuracy of 85.2%, thereby providing a novel tool for large-scale, precision monitoring and management [35]. Ghobadifar et al. used RVI, SDI14, and SDI—specific vegetation indices derived from SPOT satellite imagery—to detect healthy plants and those infected with sheath blight; additionally, the spatial distribution of infected crops in the field can be revealed by assessing leaf greenness, enabling a clear differentiation between corn sheath blight and brown planthopper damage [46]. Based on meteorological data and high-resolution satellite remote sensing imagery, Lu Baihui applied statistical methods to provide early warnings for corn pests and diseases—including red spider mite infestations, large spot disease, and armyworm outbreaks—with an accuracy exceeding 80% [49]. Richard, based on multi-temporal hyperspectral satellite data as well as meteorological and environmental information, constructed a dynamic change model of corn armyworm using three plant-canopy indices and established a dynamic monitoring and evaluation method for this pest [21]. These studies not only confirm the effectiveness of satellite remote sensing in monitoring and early warning of major corn pests and diseases but also provide critical technical support for establishing an “air-space-ground” integrated monitoring

network, particularly demonstrating irreplaceable advantages in long-term, large-scale dynamic monitoring.

Satellite remote sensing monitoring of pests and diseases in rice and corn is relatively common, whereas research on soybean pests and diseases remains limited. However, at present, satellite remote sensing monitoring platforms are primarily used after the onset of pests and diseases, focusing on assessing the extent of damage to support agricultural insurance claims. There are still certain limitations. First, regarding the model construction accuracy, although machine learning and deep learning algorithms are widely used, the adaptability and stability of these models across different regions, crop types, and environmental conditions require further validation. Second, multi-scale data fusion technology remains in the developmental stage. How to effectively integrate satellite remote sensing data, meteorological data, and ground observation data to improve the accuracy and timeliness of pest and disease monitoring remains an urgent issue to be addressed. Therefore, to accurately predict the occurrence of grain crop pests and diseases, further research should focus on multi-source remote sensing data fusion for monitoring, and precise monitoring models for crop pests and diseases should be developed to reduce economic losses caused by these outbreaks.

4. Methods for Constructing Monitoring and Forecasting Models for Pest and Disease Outbreaks in Grain Crops

Apart from the technical platform, the analytical methods applied to spectral data are equally crucial for effective monitoring. These methods can be broadly classified into statistical analysis models, computational (machine/deep learning) models, and methods combined with physiology. Each of these methods has its own unique philosophical foundation and applicable scope.

The high dimensionality of hyperspectral data presents both opportunity and the “curse of dimensionality.” Statistical models (e.g., PLSR, PCA-based regression) are foundational, excelling in establishing parsimonious relationships between a few selected spectral indices and biotic stress levels when underlying correlations are strong and linear. They are interpretable and computationally efficient. However, their performance plateaus with complex, nonlinear interactions inherent in plant–pathogen systems.

Computational models, including classical machine learning (e.g., SVM, RF) and deep learning (e.g., CNN, 1D-CNN), address this limitation. SVM and RF are robust to high-dimensional data and can model nonlinearities, with RF offering valuable feature importance metrics. The advent of deep learning, particularly convolutional architectures, represents a paradigm shift. 1D-CNNs treat spectra as sequential data, automatically learning hierarchical spectral features without manual feature engineering, while 2D/3D-CNNs exploit spatial-spectral contexts in imaging data. These models excel at pattern recognition but often function as “black boxes,” requiring large datasets and offering less intuitive physiological insight.

Physiology-integrated approaches emerge as a complementary frontier, aiming to ground spectral patterns in causative biological mechanisms (e.g., linking specific spectral shifts to chlorophyll fluorescence decay or phenolic compound accumulation). This enhances model interpretability and holds promise for detecting pre-visual stress.

The following sections and Table 3 detail representative applications within these methodological frameworks. The table synthesizes the crop, pathogen, data source, core method, and performance, providing a concise overview, while the textual discussion focuses on elucidating the comparative strengths, limitations, and evolutionary trajectory of these approaches.

Table 3. Summary of methodologies for monitoring and forecasting models of pests and diseases in grain crops.

Crop	Pathogen/Pest/Reference	Data Source/Features	Core Method
Statistical Analysis Models			
Rice	Rice leaf roller [50] Brown spot [49] Rice blast [51]	Spectral data Spectral data Hyperspectral remote sensing	PLS, Multiple stepwise regression Multiple stepwise regression, PCR, minimum norm estimation Spectral index linear regression, SVM
Maize	Rust [52]	Hyperspectral remote sensing	Vegetation index models, SVM
Soybean	Gray spot, bacterial blight [53]	Hyperspectral technology	PCA for optimal spectral index extraction
Computational Models: Classical ML & Deep Learning			
Rice	Rice blast [54]	Hyperspectral data	CARS-PCA-SVM
	Leaf diseases [55]	Disease images	CNN feature extraction + SVM classification
	Rice leaf roller, rice stem borer [56]	Pest images	YOLOv5
	Pests & diseases [57]	Image data	Two-stage small CNN, Adapted VGG16/InceptionV3
	Diseases [58]	Multi-source data	WOA-optimized Multi-task LSTM
	Leaf diseases, 6 types [59] Brown planthopper [60]	Large-scale disease image dataset Pest images	Ensemble model of four CNNs Two-stage Fast R-CNN
Maize	Leaf spot disease [61]	Canopy spectral data	GRRE, RF
	Large spot disease [62]	Hyperspectral data	1D-CNN
	Diseases, 6 major types [63]	Disease images	ECA-enhanced ResNet50
Wheat	Powdery mildew [64]	Wheat canopy hyperspectral data	MC-CARS-SPA-RFR framework
	Fusarium head blight [65]	Three-year experimental data	Novel spectral indices & optimal algorithm
	Fusarium head blight [66]	Lab hyperspectral images	Deep learning for pixel-wise classification
Soybean	Mosaic virus [67]	Hyperspectral imaging	CNN-LSTM-Attention hybrid model
Crops	Diseases [68]	Disease leaf images	Grouped attention module for semantic segmentation
Other Monitoring, Predictive, and Analytical Methods			
Rice	Bacterial blight [69]	Chlorophyll fluorescence parameters	Analysis of photosynthetic performance & fluorescence
Wheat	Stripe rust, latent stage [70]	Hyperspectral data & dual real-time PCR	R_2nd modeling combined with molecular quantification
Maize	Southern leaf spot [71]	Infrared spectroscopy	Analysis of molecular structural

4.1. Statistical Analysis Model

Statistical analysis models are widely favored by researchers due to their straightforward theoretical foundations and computational convenience. These models excel at establishing parsimonious relationships between selected spectral indices and biotic stress levels when correlations are strong and linear [72]. However, they require large volumes of data, demand high data quality, and exhibit limited generalizability.

Typical applications include linear regression, partial least squares (PLS), and principal component analysis (PCA) approaches. For instance, by evaluating 26 existing spectral indices, Nandita et al. utilized hyperspectral remote sensing technology to characterize and assess rice blast severity, establishing a linear regression prediction model with R^2 values ranging from 0.48 to 0.85. The optimal spectral indices for rice blast were RBI (R1148, R1301) and NDBI (R1148, R1301), with R^2 values of 0.85 and 0.86, respectively. In multivariate models, SVM demonstrated the best performance, with a calibration R^2 of 0.99 and a validation R^2 of 0.94 [51]. PLS-based methods, including PLS discriminant analysis (PLS-DA), have been employed for disease detection with variable success, with accuracies ranging from 66.67% for rice leaf blast [73] to over 94% for soybean disease grading [53]. These variations highlight the sensitivity of statistical models to data preprocessing choices and disease complexity.

A critical limitation of these approaches is their performance instability across different disease scenarios, with R^2 values fluctuating widely (0.48–0.99) depending on the specific application context [51]. Moreover, they struggle with the high dimensionality and inherent complexity of hyperspectral data, necessitating the development of more advanced computational approaches. Representative statistical analysis studies are summarized in Table 2,

which details their target crops, methods, and performance metrics. In addition, statistical analysis models lack the capacity to capture multidimensional nonlinear relationships and struggle to accommodate the inherent complexity of hyperspectral data, highlighting the necessity of shifting research focus toward machine learning models that offer advantages in feature auto-extraction, small-sample adaptability, and nonlinear modeling.

4.2. Computational Models

In summary, classical machine learning models (Computational models), encompassing both classical machine learning and deep learning architectures, address the limitations of statistical approaches by offering greater flexibility in handling high-dimensional data and modeling nonlinear relationships.

Scholars have carried out extensive research on the application of machine learning in the domains of crop disease identification and variety discrimination: Moshou et al. [74] pioneered the integration of spectral analysis and neural networks to detect wheat stripe rust based on the reflectance properties of healthy and infected wheat leaves. Following the evaluation of 5137 leaf spectra, the classification accuracy ranged from 95% to 99%; Murat et al. [75] extracted 16 morphological features of soybeans and compared four classification models via 10-fold cross-validation, concluding that SVM exhibited the optimal performance with an identification accuracy of 93.13%; Cinar et al. [76] constructed a rice image dataset comprising 5 varieties and 75,000 samples, extracted 106-dimensional multi-modal features, and compared six algorithms. The results demonstrated that all models achieved an accuracy exceeding 97%, among which the MLP model ranked first with a recognition rate of 99.91%. Kang et al. [54] employed Principal Component Analysis (PCA) and Competitive Adaptive Reweighted Sampling (CARS) algorithms for feature variable selection. An early hyperspectral CARS-PCA-Support Vector Machine (SVM) detection model for rice blast disease was developed, achieving an accuracy of 94.29% or higher [54]. Jiang et al. [55] addressed the problem of rice leaf disease identification by integrating a CNN with SVM. They extracted features from rice leaf disease images using a CNN and subsequently employed SVM for classification and prediction. The average correct recognition rate of the model reached 96.8% [55]. Adam et al. found that after measuring canopy height spectral data using a portable spectrometer and analyzing the data with guided Regularized Random Forest (GRRF) and traditional Random Forest (RF) classification algorithms, the overall classification accuracies of the two algorithms were 89.7% and 81.8%, respectively, in the context of corn leaf spot disease crop classification research [61]. Zi applied MC preprocessing to hyperspectral data collected from the wheat canopy during the flowering to grain-filling stages, integrated the CARS-SPA method for feature selection, and established an RFR-based estimation model. The proposed MC-CARS-SPA-RFR framework enhanced the accuracy of remote sensing estimation for wheat powdery mildew disease index (mDI), achieving an R^2 of approximately 0.85–14% higher than that of the original spectral model—and enabling high-precision, dynamic monitoring of disease progression throughout the critical growth period [64]. Zong proposed a CNN-LSTM hybrid model integrated with an attention mechanism for the early detection of soybean mosaic virus using hyperspectral imaging [67]. The model achieved a detection accuracy of 90.74% as early as two days post-inoculation, demonstrating significant performance improvements over conventional RGB-based methods [67]. Although machine learning models are well-established, the selection of handcrafted features can introduce bias into classical machine learning algorithms, leading to suboptimal modeling performance.

Have become well-established in the field of crop pest and disease identification. By combining feature selection algorithms such as PCA, CARS, and SPA, model accuracy can be effectively improved, as demonstrated by results of 94.29% for rice blast detection

and 89.7% for corn leaf spot classification. However, these models still have significant limitations: on the one hand, they rely on handcrafted feature engineering, and the feature extraction process is susceptible to subjective bias; on the other hand, they have limited capacity to model complex nonlinear relationships, making it difficult to adaptively learn deep features. In contrast, deep learning models such as YOLOv5 can automatically extract multi-scale features through an end-to-end learning mechanism, achieving over 90% accuracy in the rice-insect identification task and demonstrating greater robustness and adaptability. This provides theoretical and technical support for the further application of deep learning in intelligent pest and disease monitoring.

Deep models emphasize the importance of feature learning by leveraging big data to automatically learn representative features, thereby addressing key limitations of classical machine learning models and enabling more effective identification and classification of crop pests and diseases. For example, Liang et al. [56] independently developed a rice insect recognition model and a rice insect imaging monitoring device based on the YOLOv5 algorithm for acquiring rice pest images. The recognition accuracy for the rice leaf roller reached 91.67%, and that for the rice stem borer reached 93.39% [56]. Rahman et al. used CNN models to investigate rice pests and diseases, innovatively designing a two-stage small CNN architecture and adapting architectures such as VGG16 and InceptionV3, which significantly reduced the model size while achieving an accuracy of 93.3% [57]. Zhong et al. proposed a grouped attention module to construct an accurate real-time crop disease leaf semantic segmentation model by integrating the key strengths of two major types of semantic segmentation frameworks, achieving a pixel accuracy of 93.9% [68]. Cao et al. proposed a Multi-task Learning Long Short-Term Memory model optimized by the Whale Optimization Algorithm (WOA) to predict the disease index and latency of rice diseases, achieving predicted R^2 values of 0.93 and 0.85, respectively [58]. Prameetha Pai [59] developed an ensemble model comprising four CNN, which was trained on a large-scale dataset encompassing six distinct types of rice leaf diseases. The resulting model delivers robust, practical, and scalable diagnostic performance, demonstrating a lower misclassification rate compared to any individual constituent model [59]. He et al. conducted image detection of the rice brown planthopper using a two-stage Fast R-CNN detection algorithm, achieving average accuracy rates of 94.64% and 92.92%, respectively, demonstrating its applicability for detecting planthoppers across different population densities and developmental stages [60]. Based on three years of experimental data, Zhang et al. developed novel spectral indices and integrated an optimal algorithm, thereby improving the detection accuracy of Fusarium head blight in wheat to 91.4% and establishing a robust and effective approach for the precise diagnosis of crop diseases [65]. Aravind employed a deep learning model to perform pixel-wise classification on laboratory-acquired hyperspectral images of wheat canopies, achieving 100% accuracy in identifying Fusarium head blight infection zones and demonstrating the potential for early field diagnosis (it is worth noting that this high accuracy was achieved using a limited dataset under controlled laboratory conditions, and the generalization capability for field applications therefore requires further validation) [66]. Lu proposed a hyperspectral classification model based on a one-dimensional convolutional neural network (1D-CNN) for early detection of corn large spot disease, achieving an identification accuracy of 99.61% [62]. Xu proposed an enhanced ResNet50-based model integrated with the ECA channel attention mechanism, which achieved an accuracy of 96.02% in classifying six major types of corn diseases, thereby enabling efficient image-based rapid diagnosis in field conditions [63].

In summary, deep learning models have demonstrated significant advantages in crop pest and disease identification by enabling high-precision target detection, semantic segmentation, and disease prediction through end-to-end feature learning and data-driven approaches. How-

ever, these methods primarily rely on external morphological feature analysis and have certain limitations: first, they are unable to detect early physiological and biochemical changes caused by pests and diseases; second, they lack diagnostic capability for latent infections or internal physiological disorders. In contrast, physiological and biochemical monitoring methods can detect crop health status earlier and more directly by analyzing intrinsic indicators such as enzyme activity (e.g., peroxidase), metabolites (e.g., volatile organic compounds), and physiological parameters (e.g., chlorophyll fluorescence), thereby providing additional dimensions for pest and disease early warning. Future research should explore the integration of deep learning with physiological and biochemical sensing technologies to develop a multimodal, multi-scale crop health monitoring system capable of enabling comprehensive diagnosis from phenotype to physiology.

4.3. Other Monitoring, Predictive, and Analytical Methods

The physiological and biochemical mechanisms elicited in response to pest and disease infestation—including disruptions of leaf pigment systems, impairments of cellular structures, alterations in gene expression profiles, and modifications of metabolite compositions—serve as the biological underpinnings for the concomitant variations in spectral characteristics. Monitoring strategies that integrate such biochemical insights with spectral data thus constitute a unique class of complementary approaches. Distinct from statistical and computational models that predominantly focus on external morphological traits and correlative feature relationships, these strategies incorporate intrinsic causal biological information, thereby transcending the limitations of surface-level correlation analysis. This integration establishes a multimodal analytical framework that links the “why” of spectral signature variations (e.g., underlying physiological mechanisms) with the “what” of detected spectral signals (e.g., quantitative spectral data). Such synergy not only augments the interpretability of monitoring outcomes but also facilitates the early detection of pre-symptomatic physiological stress in crops. Consequently, the integration of crop physiological principles with spectral response characteristics has driven substantial advancements and broadened a wide range of application scenarios for precision monitoring and forecasting in grain crop protection. Scholars have developed a range of high-precision inversion models by integrating hyperspectral imaging technology with physiological indicators such as chlorophyll fluorescence, enzyme activity, and metabolite levels [77]. For example, Hao et al. demonstrated that bacterial blight infection reduces photosynthetic performance in rice and significantly affects chlorophyll fluorescence parameters, including F_m and Φ_n , highlighting the potential for non-destructive crop disease monitoring through chlorophyll fluorescence [69]. Qi Liu developed an integrated method combining dual real-time PCR for Pst quantification and second-derivative reflectance (R_{2nd}) modeling from hyperspectral data to detect latent infections of wheat stripe rust following inoculation [70]. This approach lowered the minimum detection limit (MDL) of *Puccinia striiformis* f. sp. *tritici* (Pst) to 0.7 and achieved an IBK classification accuracy of 91.7%, enabling synchronous, precise early warning of the pathogen during the latent stage through combined spectral and molecular analysis [70]. Shi et al. [71] employed infrared spectroscopy to analyze maize leaves infected with southern leaf spot disease, successfully obtaining molecular structural information from the diseased tissues. The results showed that the protein structure in corn leaves changed during growth and metabolism, shifting from a β -sheet conformation to a β -turn conformation, thereby providing a new perspective for understanding the disease mechanism [71].

These studies not only revealed the intrinsic response mechanisms of crops under pest and disease stress, such as reduced photosynthetic performance and protein conformational changes (from β -sheet to β -turn), but also verified the feasibility of physiological-

spectral integrated modeling. However, existing studies have predominantly focused on single physiological indicators or specific disease stages, failing to systematically integrate multi-dimensional information such as physiological and biochemical parameters, spectral responses, and morphological features, and lacking a universal model framework applicable across crops and diseases. In the future, it will be essential to develop an intelligent monitoring system that integrates multimodal information across “physiological mechanisms, spectral features, and image phenotypes,” combining the strengths of deep learning with mechanistic models to enable dynamic early warning of pests and diseases from the molecular to the population level, thereby providing more comprehensive technical support for precision agriculture.

5. Conclusions

(1) Currently, mainstream monitoring platforms have become increasingly diversified, with ground-based remote sensing, UAV remote sensing, and satellite remote sensing platforms all playing significant roles in the research on pest and disease prediction for grain crops. The large-scale outbreak of pests and diseases in grain crops poses a significant threat to food security and results in substantial economic losses. A single monitoring platform is insufficient to meet the demands for precise pest and disease monitoring in modern agriculture. In the future, a “space-air-ground” coordinated multi-platform monitoring network should be established: satellite remote sensing will enable large-scale, periodic macro-level monitoring, providing insights into regional trends of pest and disease outbreaks. UAV remote sensing enables fine-scale scanning of key areas, allowing for precise identification at the field level. Ground-based remote sensing is employed for fixed-point observation of representative sample plots to obtain high-precision physiological and biochemical parameters. By establishing a multi-source data fusion algorithm, seamless integration and complementary advantages of monitoring data from different platforms are achieved. At the same time, an intelligent data assimilation system should be developed to deeply integrate remote sensing data with ground observations, meteorological data, etc., to build a spatio-temporal continuous monitoring database of grain crop pests and diseases, clarify the multi-element coordinated identification and response mechanism of pests and diseases, source, host, environment, etc., and provide comprehensive data support for precise control.

(2) In the monitoring of grain crop pests and diseases, various models based on statistical data analysis have demonstrated high accuracy in detecting either diseases or pests. Nevertheless, a significant limitation of most existing models is their reliance on a single data type, which poses considerable challenges for application in real-world agricultural settings. Field environments are inherently complex and dynamic, where variables such as light conditions, crop varieties, and growth stages can substantially affect monitoring outcomes. Moreover, pest and disease outbreaks result from the combined effects of multiple interacting factors, making it difficult to fully capture their occurrence patterns based solely on morphological or spectral characteristics. Therefore, future model development should focus on the integration of multiple factors by incorporating multidimensional information—such as physiological and biochemical indicators (e.g., defense enzyme activity, secondary metabolites), environmental conditions (e.g., temperature and humidity, soil properties), and agronomic practices (e.g., planting density, water and fertilizer management)—into the modeling framework, thereby enhancing the precise identification of specific characteristics associated with grain crop pests and diseases. Particular attention should be paid to the integration of mechanistic models and data-driven models: mechanistic models can elucidate the biological mechanisms underlying pest and disease outbreaks, whereas data-driven models are capable of identifying complex patterns from large-scale monitoring data. The integration of the two approaches not only enhances model interpretability but also improves predictive accuracy. In addition, lightweight

models tailored to edge computing should be developed to enable the deployment of advanced algorithms on field-based smart terminals, thereby effectively supporting the frontline of agricultural production.

(3) This imposes higher demands on pest and disease monitoring and early warning, making it particularly urgent to accelerate the establishment of an efficient and precise system for monitoring pests and diseases in grain crops. With the rapid advancement of remote sensing technology, artificial intelligence, and biosensing technology in agriculture, there is a historic opportunity to develop a new generation of intelligent pest and disease early warning systems. First, multi-platform collaboration should be enhanced by integrating the extensive coverage of satellite remote sensing, the flexible mobility of UAV aerial photography, and the precise detection capability of ground sensors, thereby forming a three-dimensional monitoring network. Second, intelligent analysis should be strengthened by leveraging advanced technologies such as deep learning and knowledge graphs to enable automated processing of multi-source data and support intelligent decision-making. Finally, precision services should be enhanced through the integration of Internet of Things and cloud computing technologies to establish a closed-loop management system encompassing “monitoring–early warning–prevention and control,” thereby enabling the delivery of customized prevention and control strategies for diverse regions and crop types. Special attention should be given to the dynamic update mechanism of the early warning model, and the accuracy and timeliness of predictions should be continuously enhanced through the integration of new technologies and emerging data. At the same time, the agricultural technology extension system should be strengthened to facilitate the rapid transformation of scientific research achievements into productive forces and provide robust support for ensuring national food security and advancing green agricultural development.

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Abbreviations

The following abbreviations are used in this manuscript:

MLN	Maize lethal necrosis
NDRE	Normalized difference red edge index
NDVI	Normalized difference vegetation index
GNDVI	Green normalized difference vegetation index
UAV	Unmanned aerial vehicle
CNN	Convolutional neural network
PNN	Product-based neural networks
NCLB	Northern corn leaf blight

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