Hyperspectral Remote Sensing for Monitoring Crop Disease

Applications, challenges, and perspectives

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Crop disease presents significant threats to global food security and agricultural sustainability. Traditional monitoring methods, reliant on visual inspections and laboratory analyses, are labor intensive and unsuitable for large-scale implementation. Hyperspectral remote sensing has emerged as a promising tool for operational crop disease monitoring. Here, we provide a broad review, starting with a hyperspectral-based description of observable symptoms of common crop disease and then examining hyperspectral features, including spectral and textural features, pigment light absorption, solar-induced chlorophyll fluorescence (SIF), temporal information, and auxiliary data. We also analyze the algorithms used for disease detection, including traditional statistical methods, machine learning (ML)-based methods, and physically based methods. The review highlights the effectiveness of these methods in distinguishing various stressors, detecting early disease, assessing crop resistance, and monitoring large-scale disease. Additionally, we present two case studies of uncrewed aerial vehicle (UAV)-based hyperspectral imaging for maize leaf spot monitoring. Based on a quantitative literature review, we summarize current research trends. Future research should emphasize integrating physical models with deep learning (DL), ensuring the sensitivity and robustness of spectral features and promoting international data sharing.

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INTRODUCTION

Crop disease causes substantial economic damage globally, posing a serious risk to food security and agricultural sustainability [1]. In large-scale farming, preventing disease spread is crucial as curative treatments are often economically and logistically unfeasible once outbreaks become widespread [2]. Early detection and timely intervention are therefore essential. Conventional methods for monitoring crop disease primarily rely on in situ visual inspections. This process requires several professionals, which is subjective, time consuming, and labor intensive. Remote sensing is a promising tool for monitoring disease because it offers an objective, rapid, and nondestructive means of collecting data from leaf to global scale [3].

Hyperspectral remote sensing, a subset of remote sensing technologies, offers high spectral resolution and has rapidly evolved into an effective tool for agricultural research [4]. The hyperspectral sensors can collect a distinct spectral signature for each captured target at high spectral resolutions <2.5 nm, consisting of reflectance measurements in hundreds of contiguous wavelength channels [5]. It is noted that a few commercial handheld systems even achieve resolutions below 1 nm. Narrow wavebands of hyperspectral sensing systems explain their widespread use in phenotyping [6], [7]. This unique property of hyperspectral remote sensing allows for high sensitivity to subtle crop changes caused by disease. For instance, this technique has been widely used to monitor sugar beet root rot [8], sugar beet leaf spot [9], potato bacterial blight [10], and wheat yellow rust [11], [12].

As hyperspectral sensors and data analysis methods for crop disease monitoring have developed, numerous studies have reviewed advancements in this field from various perspectives. Mahlein et al. [13] first explored the factors that make hyperspectral sensors more favorable for detecting crop disease than other sensors. Zhang et al. [14] provided a workflow for using hyperspectral technologies in analyzing crop disease. Terentev et al. [15] analyzed the current state of hyperspectral remote sensing for early detection of crop disease in four types of crops, including oil palm, citrus crops, the Solanaceae (nightshade) family, and wheat. Paux et al. [16] focused on identifying candidate genes that could be further characterized to identify relevant alleles for breeding programs. Zhu et al. [17] highlighted the transformative potential of UAV-based remote sensing and DL in crop disease and pest management. These studies have made important contributions, but they lack a clear framework for identifying disease-related hyperspectral features and practical case studies.

This review explores the capabilities of hyperspectral remote sensing features for crop disease monitoring and proposes a structured approach for selecting hyperspectral features sensitive to crop disease. Additionally, we present two case studies of UAV-based hyperspectral imaging in maize leaf spot monitoring to demonstrate the potential of these technologies and methods.

The remaining content of this article is organized as follows. The "Plant Disease Basics" section provides an overview of the fundamental definitions and common symptoms associated with crop disease. The "Hyperspectral Features" section explores a range of relevant hyperspectral features for monitoring crop disease and develops four criteria for selected features. The "Algorithms for Modeling Crop Disease" section reviews the algorithms used in monitoring crop disease using hyperspectral data. The "Areas of Application" section presents practical applications of hyperspectral monitoring in crop disease management. The "Case Studies" section shows two case studies. The "Challenges and Future Perspectives" section discusses the challenges and future perspectives in utilizing hyperspectral remote sensing for disease monitoring. Finally, the "Conclusion" section summarizes a general overview and conclusion.

PLANT DISEASE BASICS

Crops face various environmental stresses, which impact their growth, development, survival, and final yield. These stresses are classified into biotic and abiotic categories. Abiotic stresses, such as solar radiation, salinity, waterlogging, nutrient shortages, temperature extremes, and heavy metals, can affect the metabolism, growth, and development of the crop [18], [19]. In contrast, biotic stresses arise from interactions between crops and other living organisms, such as fungal pathogens, weeds, insect pests, nematodes, protists, viruses, and viroids [20]. For the purpose of this review, the term "crop disease" refers specifically to biotic stress, as defined in Nutter et al. [21].

Disease responses in crops result from complex interactions among various organisms. These interactions can affect different crop components, including roots, stems, leaves, and fruits, and may have both direct and indirect impacts on crop physiology and biochemistry [Figure 1(a)]. For example, viruses can cause damage by inducing pigment degradation, structural wilting, and necrosis, which may lead to nutrient deficiencies, such as phosphorus deficiency [22]. Fungal pathogens can cause a diverse range of diseases, including anthracnose, leaf spot, rust, and wilt. These symptoms can be monitored as changes in canopy reflectance [23]. In addition, the temporal aspect of disease symptoms is important. Short-term disease manifestations often reflect changes in photosynthesis, respiration, and transpiration rates. In contrast, long-term infections can have more persistent effects on crop growth and development [24].

Crop responses to disease are typically continuous but often exhibit nonlinear characteristics [25]. Responses to disease can be divided into three phases based on the severity and duration of the stressors. Taking the case of rice leaf blast as an example, the disease starts with a few watery lesions (usually one or two) on infected leaves, which are often difficult to monitor under field conditions. In the mild stage, several small brown spindle lesions appear on the leaf surface. The surface generally appears normal, except for the necrotic lesions. As the disease progresses, the severe infection stage features multiple distinct fusiform plaques on the leaf surface, accompanied by wilting and yellowing around the lesions [26].

It is important to note that the same disease can produce different symptoms depending on environmental conditions and the developmental stage of the crop. As shown in Figure S1 in the supplementary materials available at https://doi.org/10.1109/MGRS.2025.3603640, different diseases may also lead to similar symptoms. Therefore, a thorough understanding of the physiological responses of crops to specific diseases is crucial for accurate disease identification and effective mitigation strategies.

HYPERSPECTRAL FEATURES

Hyperspectral features calculated from hyperspectral reflectance can be used to identify, analyze, and classify different materials or conditions. Since the early hyperspectral work of Baret et al. [27], numerous features have been proposed for assessing crop structure and physiology

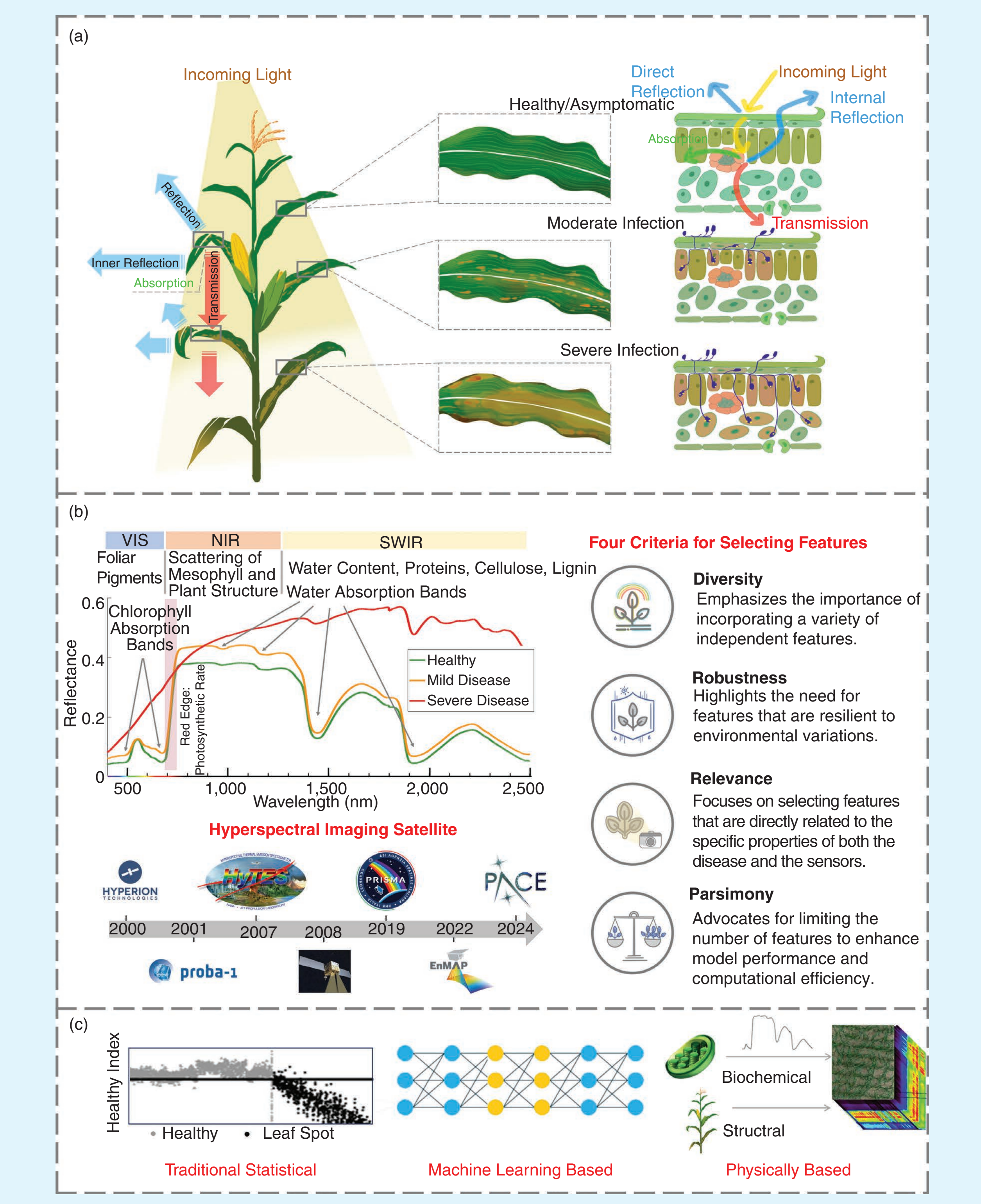

FIGURE 1. A comprehensive framework of remote sensing-based crop disease monitoring: from crop-disease interaction to disease feature and modeling analysis algorithms. (a) Crop-disease and crop-light interactions under different disease severity. (b) Spectral response and feature selection criteria. (c) Algorithms for monitoring disease. VIS: visible reflectance; NIR: near-infrared reflectance; SWIR: shortwave IR reflectance.

changes and monitoring crop disease. This review divides hyperspectral features into spectral, textural, and biophysical features such as pigment light absorption and SIF (refer to Table 1). These features, when collected over multiple time points, can provide valuable temporal information. Moreover, incorporating auxiliary data from other sources can enhance disease monitoring accuracy by supplementing the hyperspectral data.

SPECTRAL FEATURES

The visible (VIS) and near-infrared (NIR) spectral domains are commonly used to monitor crop disease [28], [29], [30], [31], [32] as they are highly sensitive to changes in pigments, photosynthesis, and water content caused by disease. Chlorophyll, which gives vegetation its green color, strongly absorbs in the red (650–700 nm) and blue (400–500 nm) spectral regions. It has maximum reflectance in the green wavelengths (560 nm), as shown in Figure 1(b). Anthocyanins, reflecting strongly in red wavelengths, have an absorption maximum at approximately 530 nm. Similarly, the red-edge region (680–780 nm) is sensitive to changes in the photosynthetic rate [33], [34]. The NIR region is sensitive to foliar and canopy structure, while the shortwave IR (SWIR) region is particularly sensitive to leaf water content.

Hyperspectral reflectance refers to an object's ability to reflect light across various wavelengths, which is captured by hyperspectral sensors. Commercial hyperspectral sensors on the market have spectral capabilities that cover the entire range, or selected portions, of the electromagnetic spectrum from 400 to 2,500 nm. They can retrieve between 30 and more than 2,000 individual bands [35]. Each object or material exhibits a unique reflectance pattern at specific wavelengths, forming a distinct spectral "fingerprint" that can be used to identify or differentiate between healthy crops or diseases. While hyperspectral reflectance provides rich spectral information, it is significantly influenced by atmospheric and lighting conditions.

Vegetation indices (VIs) are often used to compensate for some of the effects of environmental factors and are widely employed to characterize crop information. Many VIs have been proposed since the early 1970s to monitor crop biophysical, biochemical, and physiological properties [47]. These properties are closely correlated with crop disease, making VIs practical tools for monitoring disease (see Table S1 in the supplementary materials available at https://doi.org/10.1109/MGRS.2025.3603640). The most basic VIs are obtained from an algebraic combination of spectral reflectance [48]. Among these, the photochemical reflectance index (PRI) is one of the most commonly used indices for quantifying spectral changes caused by disease. PRI is based on variations in xanthophyll concentration and pigment pool sizes, enabling it to effectively track light-use efficiency and photosynthetic performance [49]. Variants of PRI, such as normalized PRI (PRI_n) and modified PRI, have also been used for disease monitoring [39], [50], [51]. Additionally, several VIs sensitive to crop pigments have been employed for disease monitoring. These include the normalized phaeophyte index [52], Vogelmann index [53], transformed chlorophyll absorption ratio/optimized soil adjusted VI [54], Lichtenthaler et al. [55], and

TABLE 1. HYPERSPECTRAL FEATURES FOR MONITORING CROP DISEASE.

	ADVANTAGES	DISADVANTAGES	RELATED STUDIES
SPECTRAL FEATURES			
Hyperspectral reflectance Spectrum transformation WFs VIs	Simple calculation	Poor transferability Mixed spectrum	[10], [36]
SPATIAL FEATURES			
Textural features	Represents the spatial pattern	Affected by spatial resolution Requires imaging sensors	[37], [38]
PIGMENT LIGHT ABSORPTION			
Anthocyanins Chlorophylls Xanthophyll V + A+Z pool Carotenoids	Early response Good transferability Robustness	Complexity of physically based models	[39], [40]
FLUORESCENCE EMISSION			
Solar-induced fluorescence	Early response	Weak signals High spectral resolution Lack of disease specificity	[41], [42]
TEMPORAL INFORMATION	Minimized confounding effects	Increased workload	[43]
AUXILIARY DATA			
Vegetation temperature	Early response	Atmospheric correction issue Complex retrieval Lack of disease specificity	[41], [44]
Structural information	Surface penetrating	Lack of chemical information	[45], [46]

pigment-specific normalized difference for chlorophyll a [56]. Likewise, VIs sensitive to water content, including the water index, disease-water stress index, and normalized difference water index, have been utilized to monitor diseases [57], [58], [59]. Although VIs are useful in many cases, they generally ignore the finer spectral details that hyperspectral data can offer. Thus, while these indices are practical, they are inherently suboptimal for hyperspectral applications that require a more nuanced understanding of crop health [60].

The red-edge inflection point and three-edge parameters are also used to capture unique spectral characteristics of crop disease. These indices encompass position, amplitude, and area within wavelength regions of substantial spectral variability [61], [62]. For instance, Lin et al. [63] investigated the sensitivity of 36 three-edge parameters to rice sheath blight. They highlighted that the ratio index of the red-edge area to the green-peak area was the most important feature for distinguishing foliar sheath lesions from foliar blade lesions. Feng et al. [64] demonstrated that the sum of the first derivatives within the blue edge was significantly correlated with the severity of wheat powdery mildew. While these VIs can represent changes in crop health to some extent, they generally lack disease specificity.

To monitor a particular disease, disease-specific indices are generally developed after evaluating the sensitivity of spectra to the specific symptom associated with the target disease. For example, the healthy index was created to monitor sugar beet diseases by testing all possible combinations of a single wavelength and a normalized wavelength difference [65]. The yellow rust spectral index was designed to estimate the severity of wheat yellow rust [66], and the *Fusarium* head blight classification index was developed to classify healthy and diseased areas of wheat spikelets [67]. Developing such indices requires a clear understanding of how hyperspectral spectra respond to the disease symptoms. A more direct method of building VIs involves mimicking the mathematical form of classical indices and exhausting all possible band combinations. For example, Marzougui et al. [68] calculated the normalized difference spectral indices using the formula of the normalized difference vegetation index (NDVI) and all combinations of wavelengths, and Meng et al. [58] used the form of the healthy index to construct a three-band combination index. However, these disease-specific indices, derived from leaf spectral data, often do not account for the structural parameters of crops, leading to decreased accuracy when applied to canopy-level monitoring tasks [69]. Future efforts should focus on enhancing the robustness of disease-specific indices to different crop species and environmental conditions, thereby enabling real-time disease detection across agricultural landscapes.

Several transformations of the raw spectrum can also be applied to monitoring crop disease, such as the derivative transformation [70], [71] and wavelet features (WFs) [36], [59], [72], [73]. These transformations often produce features equivalent to or even more numerous than the original reflectance data. Consequently, the sensitivity and specificity of these features to crop disease require careful analysis.

TEXTURAL FEATURES

Image texture represents the distribution of pixel grayscale values and their spatial neighborhood relationships. Textural features have been applied in monitoring crop disease, including wheat powdery mildew [37], [38], [74], *Fusarium* head blight [30], [31], and yellow rust [75]. The most commonly used method for calculating textural features is based on the gray-level cooccurrence matrix (see Figure S2 in the supplementary materials available at https://doi.org/10.1109/MGRS.2025.3603640). This method allows for the extraction of various textural features, such as contrast, homogeneity, energy, and entropy [37], [38]. As a type of spatial feature, textural features can effectively monitor diseases that cause variations in leaf or canopy patterns. However, their performance depends on spatial resolution.

PIGMENT LIGHT ABSORPTION

The absorption properties of crop pigments, expressed as pigment concentration, are critical indicators of crop diseases. They reflect symptoms such as discoloration and chlorosis [39], [76]. Numerous studies have demonstrated that analyzing pigment concentration is essential for accurately detecting infected crops. It also helps distinguish symptoms caused by pathogens from those induced by water stress. Zarco-Tejada et al. [40] found that anthocyanin content was critical for distinguishing *Xylella fastidiosa* infections in olive trees from water-stress responses, while chlorophyll content (C_{ab}) was relevant in almonds. Similarly, Watt et al. [77] identified C_{ab}, carotenoid content, and leaf area index (LAI) as the most critical features for predicting the severity of *Dothistroma* needle blight in radiata pine, using UAV hyperspectral imagery. In a recent study, Poblete et al. [78] analyzed the progression of pigment concentration as symptoms worsened due to vascular pathogens in a multidate, multisite, and multispecies study. They found that pigment concentrations played different roles depending on the stage of the infection. As diseases progress, changes in pigment concentrations evolve, highlighting the importance of monitoring pigment dynamics over time to assess disease severity. These pigments can be retrieved based on radiative transfer models (RTMs), which simultaneously leverage information from the entire wavelength range [79], [80]. However, these inversion methods based on complex physical models may introduce errors [81], [82].

SOLAR-INDUCED CHLOROPHYLL FLUORESCENCE

SIF provides valuable information about photosynthetic activity, making it a crucial indicator for assessing crop health and detecting disease [83], [84], [85]. Several methods have been developed to quantify SIF at the foliar and canopy levels, including the Fraunhofer-line discrimination method

[86], RTMs [87], [88], spectral-fitting methods [89], and singular vector decomposition [90]. However, retrieving SIF from spectral images is challenging as the SIF signal under natural light conditions constitutes less than 1% of the incident energy [91]. Fortunately, recent work has shown a strong relationship between SIF quantified with subnanometer resolution [0.1–0.2-nm full width at half-maximum (FWHM)] and narrowband resolution (5.8-nm FWHM). This demonstrates that SIF can be tracked in relative terms using broader resolution sensors [92]. This has enabled the use of broader-band imaging spectrometers to quantify SIF and detect biotic stress with high accuracy [39], [40], [50]. Given the potential of SIF in disease monitoring, future research should focus on developing algorithms that can isolate SIF from other sources of variability, improving its specificity for disease monitoring.

TEMPORAL INFORMATION

Temporal information, derived from sequences of hyperspectral images over time, can significantly enhance crop disease monitoring accuracy. Such temporal data allow for identifying trends in crop growth. For example, Anderegg et al. [43] demonstrated that temporal changes in canopy spectral reflectance enabled the quantification of *Septoria tritici* blotch in various wheat germplasms. This approach minimized the confounding effects of genotype and environment. Compared to reflectance spectra obtained at individual time points, time-integrated information offers improved specificity and robustness in assessing crop disease. Temporal features can also aid in distinguishing diseases from physiological aging. Despite these advantages, few studies have investigated the use of hyperspectral data from multiperiod images for monitoring crop disease. The primary challenges in using time-series data for disease monitoring include the increased workload and cost associated with data acquisition and analysis.

AUXILIARY DATA

Multimodal collaboration is generally an efficient framework for monitoring crop disease [60]. Multimodal remote sensing data can provide a more comprehensive understanding of the complex interactions between diseases and crops. The widely used data to complement hyperspectral data for disease monitoring are thermal and lidar data. Thermal data provide insights into temperature variations and moisture stress, while lidar data offer precise 3D structural information of the crop canopy.

VEGETATION TEMPERATURE

Vegetation temperature is useful for determining transpiration rates and assessing crop health [93]. Pathogens colonize crop vessels, block sap flow, reduce transpiration, and increase canopy temperature [39], [42]. Combining vegetation temperature with hyperspectral characteristics has been employed for early disease monitoring [41], [74], [94], [95], discriminating pathogens with similar visual symptoms [96], and disentangling biotic from abiotic sources of stress [40]. Zarco-Tejada et al. [39] conducted a pioneering study using airborne hyperspectral and thermal data to analyze trees experiencing early stress caused by the bacterial pathogen *Xylella fastidiosa*. They derived indicators of vegetation temperature and the crop water stress index (CWSI) from thermal images. Additionally, they estimated canopy structural and foliar biochemical traits using RTM inversion and calculated the sensitivities of narrow-band spectral indices using hyperspectral images. All these indicators underwent multivariate analysis using ML to classify the previsual incidence and severity of the disease on a large field scale. Despite considerable advances in both satellite and UAV-based thermal sensing, challenges remain. The accuracy of thermal data is often compromised by data correction issues, making it difficult to distinguish crop stress from disease infection or the confounding effects of rapidly changing environmental conditions [97].

STRUCTURAL INFORMATION

Lidar technology can accurately obtain 3D structural information about objects, enabling the precise segmentation of crops, shadows, and crop overlap [98]. This structural information often complements hyperspectral data by addressing the issue of spectral confusion (spectral confusion arises when different materials or objects exhibit similar spectral characteristics, making it difficult to differentiate between them based solely on spectral information). By providing precise distance measurements and detailed 3D point cloud information, lidar assists in overcoming spectral confusion and enables better discrimination and identification of objects. Many studies have investigated the static and dynamic changes of structural and functional phenotypes in agriculture using lidar technology [99]. For example, lidar data have been used to segment individual trees in data preprocessing to improve the accuracy of monitoring disease with hyperspectral images [45]. Lidar metrics, such as crown volume, crown area, and various intensity-based statistics (e.g., coefficient of variation, 25th percentile, and kurtosis of crown-return intensity), have been used in models of disease classification [46]. Spatially aligning lidar and spectral data, however, remains a considerable challenge due to differences in sensor characteristics, resolution, and georeferencing [100].

FOUR CRITERIA FOR SELECTING FEATURES

The essence of remote sensing feature selection corresponds to feature engineering in computer science. Feature engineering involves selecting, creating, and transforming features from raw data to improve the performance of ML. Effective feature engineering is crucial in ML tasks as it can greatly impact models' performance and generalization ability [101]. This article identifies four simple criteria for feature selection: diversity, robustness, relevance, and parsimony.

- *Diversity:* Obtaining multiple and independent crop features, rather than only one, is essential for accurately identifying crop disease. Multiple spectral domains or sensor modalities can provide a comprehensive understanding of complex interactions between diseases and crops.
- *Robustness:* The radiance received by hyperspectral sensors is the combination of multiple radiation sources, like atmospheric and environmental conditions. Features should be robust to variations in geometry, illumination, canopy structure, and soil, which ensures a model's generalization to different spatiotemporal scales.
- *Relevance:* Features must be relevant to the target disease, helping models better capture the relationship between features and diseases for more accurate monitoring. Features should also be pertinent to the stage of the disease as different stages trigger physiological responses associated with distinct features. Additionally, features should align with the properties of the sensors. An overview of widely used spectral indices can be found in an online database (www.indexdatabase.de).
- *Parsimony:* Reducing feature dimensionality can improve model efficiency and generalization as well as decrease computational costs. But the number of features should still be kept uncertain. For example, two to four disease-specific spectral features were sufficient to identify rice leaf blasts [26], but eight spectral bands to monitor tomato spotted wilt achieved the best classification accuracy [102].

The relevance of the four criteria for feature selection can be widely observed in previous practical studies. Notably, different diseases or stages of infection may yield different feature selection outcomes. In summary, there is no perfect feature. Therefore, we recommend considering instrument attributes and disease characteristics and focusing on extracting appropriate features.

ALGORITHMS FOR MODELING CROP DISEASE

The methods used to monitor crop disease can be broadly categorized into three groups: 1) traditional statistical methods, 2) ML-based methods, and 3) physically based methods. Each of these methods has unique strengths, but they also come with inherent limitations, as detailed in Table 2. These algorithms have shown varying levels of accuracy when applied to specific crops and diseases, as detailed in Table 3. The distinction between traditional statistical approaches and ML is often debated [103]. In this study, traditional statistical methods emphasize inference—aiming to understand how hyperspectral features respond to disease. In contrast, ML methods focus on monitoring accuracy, leveraging flexible algorithms to capture complex and nonlinear relationships between spectral features and crop disease.

TRADITIONAL STATISTICAL METHODS

Over the last few decades, scientists have attempted to use single or multiple indicators to estimate the extent of disease occurrence. Univariate and multivariate regression-based algorithms have been extensively used to monitor crop diseases using hyperspectral signatures. For example, PRI exhibited a negative linear relationship with the disease index of wheat yellow rust [104]. A single VI index lacks specificity for identifying and differentiating diseases, but combining two or more spectral VIs can improve disease monitoring accuracy [9], [107]. Multivariate regression models, such as multinomial logistic regression (MLR) and partial least squares regression (PLSR), have also been used for monitoring diseases [105], [106]. These methods quickly build relationships between hyperspectral features and disease severity. However, they tend to oversimplify complex interactions between spectral data and plant physiological responses, limiting their effectiveness for detecting early-stage or subtle disease symptoms.

TABLE 2. COMPARATIVE ANALYSIS OF VARIOUS ALGORITHMS APPLIED IN HYPERSPECTRAL REMOTE SENSING FOR CROP DISEASE MONITORING.

ALGORITHMS	ADVANTAGES	DISADVANTAGES	EXEMPLARY STUDIES
TRADITIONAL STATISTICAL METHODS			
Univariate linear regression	Simple and easy to understand Suitable for selecting features	Limited to linear relationships Does not consider interactions among features Limited areas of application	[104]
Multivariate regression	Considers multiple features	Limited areas of application	[105], [106]
SAM	Considers multiple source features Computationally efficient	Sensitive to noise Performs poorly for weak spectral responses	[107]
ML-BASED METHODS			
Traditional ML	Suitable for modeling complex relationships	Requires feature selection	[108], [109]
DL	The end-to-end model Suitable for modeling complex relationships	Difficult to interpret	[102], [110]
PHYSICALLY BASED METHODS			
Synergistic integration of RTMs and ML	Leverages available physical understanding	Model errors due to the simplification of reality Accumulation of model errors	[44], [78]

SAM: spectral-angle mapper; ML: machine learning; DL: deep learning; RTM: radiative transfer model.

Classical supervised classification algorithms also have been used [111], [112], [113], including minimum distance and spectral-angle mapper (SAM). The minimum distance method uses Euclidean or Mahalanobis distances to compare pixel values with the centroid value of the sample class. SAM classifies each spectrum based on its angular similarity to the spectra of known endmembers. These methods are useful for hyperspectral classification, particularly in well-defined cases. However, these methods can struggle to differentiate between classes in complex or heterogeneous canopies, where disease symptoms overlap with healthy crop features.

In the future, traditional statistical methods should incorporate more advanced preprocessing steps to better handle noise and mixed spectra. For example, incorporating ML feature selection or dimensionality reduction techniques may improve the robustness of these methods.

MACHINE LEARNING-BASED METHODS

ML algorithms have proven to be indispensable tools for the effective monitoring of crop disease. Supervised ML classification algorithms such as linear discriminant analysis (LDA), random forest (RF), support vector machines (SVMs), stepwise discriminant analysis (SDA), multilayer perceptron, radial basis function, decision trees (DTs), and *K*-nearest neighbor (KNN), have all been widely used [58], [73], [95], [108], [109], [114], [115]. These traditional ML algorithms can capture complex relationships, but careful engineering and selection of features are required before modeling.

DL, on the other hand, simplifies the modeling process by eliminating the need for manual feature engineering [116]. Convolutional neural networks (CNNs) are particularly effective for these tasks because they can extract highly discriminatory features and leverage the spatial-contextual and spectral information contained in cubes of hyperspectral imagery data. For instance, 1D-CNNs have demonstrated a high average accuracy of 97.72% in identifying disease

TABLE 3. EXAMPLES OF HYPERSPECTRAL REMOTE SENSING METHODS FOR MONITORING CROP DISEASE.

CROP	DISEASE	PLATFORM	FEATURE	METHOD	BEST ACCURACY	REFERENCE
TRADITIONAL STATISTICAL METHODS						
Wheat	yellow rust	Handheld, airborne	Spectral	RE	–	[104]
Sugar beet	Leaf spot, powdery mildew, and rust	Leaf clip	Spectral	COC	–	[9]
ML-BASED METHODS						
Wheat	Powdery mildew	Benchtop	Spectral, textural	PLSDA	91.4%	[37]
Rice	Rice blast	Leaf clip	Spectral	ML-SFFS (ML: LDA, KNN, SVM)	Asymptomatic: 69.58% Early: 95.77% Mild: 98.65%	[26]
Wheat	*Septoria tritici* blotch	Handheld	Spectral, temporal	PLSDA	86%	[43]
Wheat	*Fusarium* head blight	Benchtop	Spectral, SIF	SVM	89%	[41]
Tomato	Spotted wilt virus	Robotic manipulator	Spectral	GAN	96.25%	[102]
Pine forests	Pine wilt disease	UAV	Spectral	3D-Res CNN	Early: 88.11%	[110]
PHYSICALLY BASED METHODS						
Holm oak	*Phytophthora*-induced symptoms	Airborne	Spectral, pigment concentration, SIF, multimodal	3D RTM, SVM, RF	71–82%	[44]
Olive	*Xylella fastidiosa*	Airborne	Spectral, pigment concentration, SIF, multimodal	3D RTM, SVM, NNE, LDA	80.9%	[39]
Olive, Almond	*Xylella fastidiosa and Verticillium dahliae*	Airborne	Spectral, pigment content, structural properties, CWSI, SIF	PRO4SAIL, SVM, RF, spectral clustering, multistage classification	92%–94%	[39]
Olive	*Xylella fastidiosa and Verticillium dahliae*	Airborne	Spectral, pigment content, structural properties, CWSI, SIF	PRO4SAIL, SVM, RF, spectral clustering, multistage classification	92%, 98%	[96]
Grape	Yellowness and esca	Leaf clip	Spectral, pigment concentration, textural	PROSPECT-D, BPNN	99% for both diseases	[120]

CWSI: crop water stress index; SIF: solar-induced fluorescence; RE: regression equation; COC: coefficient of correlation; PLSDA: partial least squares discriminant analysis; ML-SFFS: ML-based sequential floating forward selection; LDA: linear discriminant analysis; KNN: *K*-nearest neighbor; SVM: support vector machine; GAN: generative adversarial net; 3D-Res CNN: 3D convolutional neural network; RF: random forest; NNE: neural network ensemble; BPNN: back-propagation neural network. These methods have the potential to be applied across multiple crop disease scenarios, although some were originally developed and validated in specific contexts.

spots on potato leaves using hyperspectral imagery [117]. Similarly, 2D-CNNs achieved an F1 score of 0.75 and an accuracy of 74.3% when classifying hyperspectral pixels of healthy wheat heads versus those affected by *Fusarium* head blight in field conditions [118]. Furthermore, 3D-CNNs can outperform 2D-CNNs because they take advantage of the spectral dimension in hyperspectral data cubes, enabling the model to capture both spatial and spectral relationships [119]. In particular, 3D-Res CNNs achieved an overall accuracy of 88.11% in identifying pine trees infected with pine wilt disease from UAV-based hyperspectral images, with an accuracy of 72.86% for detecting early-stage infections [110]. Although CNNs models can deliver high accuracy, their performance is heavily dependent on large labeled training datasets. In agricultural remote sensing, such datasets are often limited, especially for diseases that are rare or are poorly represented in existing datasets.

PHYSICALLY BASED METHODS

Physically based methods involve radiative transfer processes to model disease monitoring. These processes are described by RTMs. RTMs have been developed to simulate the interaction of electromagnetic radiation with canopy elements (such as leaves and soil). RTMs represent the architecture of the canopy and biochemical properties of its constituents. Although crop diseases are often considered secondary variables that cannot be directly associated with the mechanisms of the radiative transfer process [121], they are closely linked to primary variables (e.g., pigment concentrations and LAI) that are directly involved in radiative transfer. This connection necessitates the integration of RTMs with either statistical or ML methods to develop robust physically based models for disease monitoring.

The physically based method is a powerful tool for estimating biophysical and biochemical variables without the need for in situ reference data. These variables are direct and interpreting indicators caused by crop disease. For example, Camino et al. [51] combined the PROSAIL model with RF to monitor *Xylella fastidiosa* infections. They used chlorophyll and anthocyanin concentrations derived from PROSAIL as inputs to RF to improve monitoring accuracy. Similarly, Hornero et al. [44] employed additional RTMs, including FLIGHT+FLUSPECT and FLIGHT+PROSPECT, to invert a broader range of crop functional traits related to oak decline, such as water content, chlorophyll, carotenoid, anthocyanin levels, fluorescence, LAI, crown temperature, and dry matter content.

In these studies, RTMs provide valuable physical constraints and domain knowledge, but they also have limitations in representing complex disease processes. Further research is needed to explore more flexible and advanced approaches for combining RTMs with ML to improve the accuracy of disease monitoring under diverse conditions.

AREAS OF APPLICATION

Research utilizing hyperspectral sensing for monitoring crop disease can be categorized into five application areas: 1) assessment of disease incidence and severity, 2) discriminating among stressors, 3) detecting disease symptoms at the early stage, 4) discriminating crop resistance in breeding, and 5) monitoring disease on a large scale. The concepts of these categories are illustrated in Figure 2. The first category serves as the fundamental task in monitoring crop diseases and has already been discussed in previous sections. To avoid redundancy, this section will instead provide an overview of the advancements in categories 2 through 5.

STRESS DISCRIMINATION

Crops are constantly exposed to various stress factors, including biotic and abiotic stress, which can affect their growth, development, and productivity. These stresses

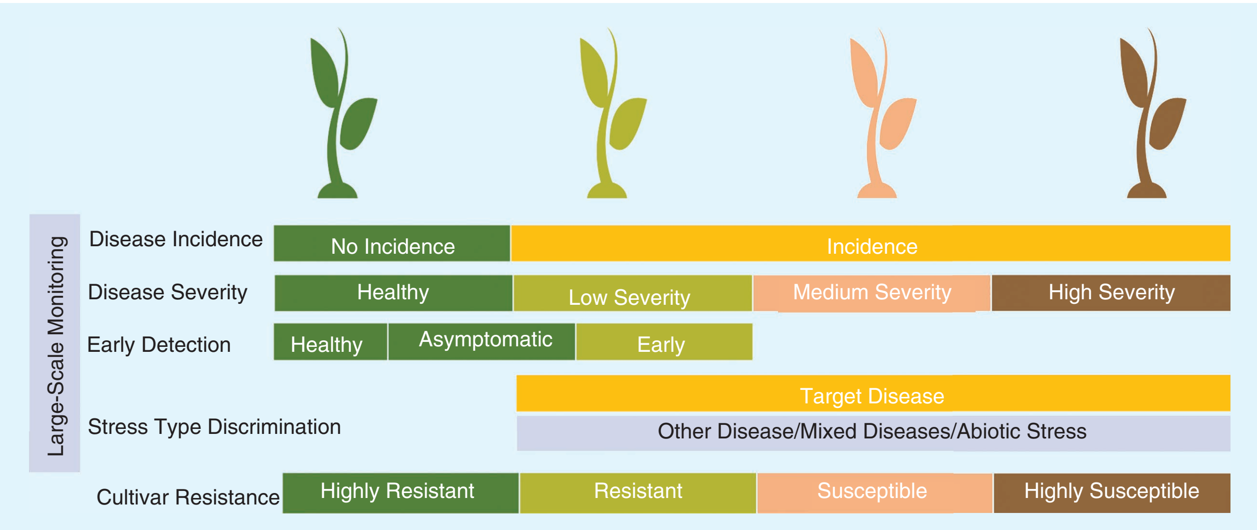

FIGURE 2. Applications of hyperspectral sensing in disease monitoring. Green, yellow-green, pink, and brown colors serve as indicators of an increase in the severity of diseases. Yellow indicates the target disease incidence. Gray indicates stress factors other than the target disease.

often manifest similar symptoms, such as discoloration and wilting. Hyperspectral remote sensing has been used to discriminate differences between symptoms induced by pathogens [96] and different types of stress in crops, including water-induced stress [40], [122], nutrient deficiency [71], [123], [124], pest and disease infestation [126], extreme weather [127], and heavy-metal toxicity [128], [129], [130]. Different types of stresses can be identified because each stressor induces unique spectral responses in the crop. For example, nutrient deficiency and yellow rust can be identified by changes in PRI [71], and drought stress and infestation have different patterns of change in reflectance in NIR and SWIR [122]. A phylodynamic approach with multistage classificatory methodology has been used for uncoupling biotic-abiotic spectral dynamics to reduce uncertainty [40]. Disease outbreaks are often influenced by factors such as climate and crop growth history [131]. The main groups of pathogens favor critical environmental factors, including high temperature, large rainfall, high relative humidity, pH, and fertility [132]. Looking ahead, integrating remote sensing data with real-time environmental and agricultural expertise holds great potential for more accurate stress discrimination.

EARLY SYMPTOM DETECTION

The accurate detection and diagnosis of the symptoms at the early stage of disease are crucial for minimizing crop yield losses and preventing the spread of disease. Researchers have recently explored the potential of using remote sensing features and spectral crop trait analysis to monitor the previsual symptoms of disease infection. A practical framework using high-resolution hyperspectral images, thermal data, and RTMs has been developed to evaluate the efficacy of detecting previsual *Xylella fastidiosa* infection [39]. The results indicated that this framework can identify disease symptoms before they are visible to the human eye. Camino et al. [51] developed a method for detecting disease that combined spatial epidemiological models and remote sensing to accurately monitor the spatial distribution of *Xylella fastidiosa* in almond orchards. These achievements represent an important step forward in early crop disease detection. Building on these successful approaches, future research should explore the complementary advantages of multisource data to enhance early disease detection capabilities.

BREEDING RESISTANCE

The development of resistant cultivars is a key strategy for controlling pathogen infection. Phenotyping is a vital step in breeding programs because it involves the qualitative characterization of how genomic expressions affect crop function within specific environments [133], [134]. Phenotypes have traditionally been visually estimated, which is laborious and time consuming and can be subjective depending on the breeder’s expertise. Image-based phenotyping offers a promising solution by enabling more objective and efficient resistance assessments [10], [68], [135], [136]. However, challenges arise from the variability in reflectance caused by genotypic diversity and fluctuating environmental conditions—key factors in resistance breeding. To address these challenges, Anderegg et al. [43] devised a spectral-temporal feature method that relies on relative changes in spectral reflectance over time. They employed two types of dynamic parameters. The first type, “key time-points,” corresponded to specific moments when predetermined criteria were met. The second type, called “change parameters,” represented either the rate or duration of a particular process. Their findings highlighted the absence of specificity and robustness in evaluating disease based only on reflectance spectra at individual time points. By tracking temporal changes in canopy reflectance during pathogenesis, this approach significantly reduces the confounding effects of genotype and environment, thus enhancing the specificity of crop disease monitoring. This approach has shown success with handheld spectroradiometers, but UAV-mounted sensors may be a more effective solution for high-throughput monitoring in the future. Additionally, integrating hyperspectral data with genomic data could lead to improved models for genotype-environment interactions.

LARGE-SCALE MONITORING

Large-scale monitoring refers to the observation and analysis of extensive geographic areas, which is crucial for understanding and managing widespread crop disease challenges. A review of the literature identified only two relevant studies that employed satellite-based hyperspectral data for monitoring crop disease. One study by Apan et al. [137] assessed several narrow-band indices derived from *EO-1* Hyperion imagery to identify sugarcane areas affected by orange rust. Another study by Dutta et al. [138] developed an integrated two-step wilt detection approach and a disease-specific spectral index for *Cajanus cajan* using the ASI-PRISMA hyperspectral dataset. Their method enabled the detection of wilt in *Cajanus cajan* plants at least two to three weeks earlier than conventional multispectral satellite imagery.

While significant progress has been made in hyperspectral disease monitoring at the leaf and field scales, applying these methods at larger scales presents both opportunities and challenges. Since 2000, seven satellites equipped with hyperspectral sensors have been launched, including *EO-1 Hyperion*, *PROBA-CHRIS*, *HyspIRI*, *HJ-1A*, *PRISMA*, *EnMAP*, and *PACE* (see Table S2 in the supplementary materials available at https://doi.org/10.1109/MGRS.2025.3603640 for details). These satellites offer valuable spectral data for monitoring crop disease over large regions. However, limitations such as lower spatial resolution and cloud cover can reduce the effectiveness of satellite-based disease monitoring. In contrast, ground-based and UAV-based hyperspectral imaging systems have demonstrated higher accuracy in crop disease detection due to their superior spatial resolution and greater operational flexibility. As a result, the future of large-scale crop disease monitoring will likely involve integrating ground-based, airborne, and satellite-based hyperspectral technologies to leverage the complementary strengths of each. Moreover, multispectral satellite data, such as those from Sentinel and Landsat, typically provide better spatial resolution than hyperspectral data. Therefore, combining multispectral and hyperspectral data can offer both high spatial and spectral resolution, greatly enhancing the accuracy of large-scale disease monitoring.

CASE STUDIES

RESPONSE TIMES OF HYPERSPECTRAL FEATURES MONITORING MAIZE LEAF SPOT DISEASE

We assessed the sensitivity of biophysical and spectral features as indicators of maize responses to leaf spot disease using high-resolution UAV hyperspectral imagery collected over a 30-day period after infection. The response time of hyperspectral features was determined using two statistical criteria: 1) 95% confidence intervals derived from a z-distribution and 2) effect size (Cohen's d). A detectable response was considered on the first day that consecutive substantial differences (effect size > 0.8) were observed between infected and healthy areas. More detailed information can be found in Bai et al. [139]. This analysis included hyperspectral features, biophysical parameters derived from the PROSAIL model, spectral reflectance, VIs, and WFs. Our results showed that the WFs provide the earliest indicator of disease onset, with detectable responses to leaf spot as soon as six days after infection (DAI 6). The VIs followed, with responses detectable by DAI 8, and the response in C_{ab} became evident by DAI 10. For example, compared to DAI 0 measurements [Figure 3(a)], the change in C_{ab} (ΔC_{ab}) first increased and then gradually decreased. The accumulation of C_{ab} in infected areas lagged behind healthy areas, with a notable difference in the C_{ab} change rate observed from DAI 10 onward. However, spectral reflectance in the 400–900-nm wavelength range was prone to noise, and no significant continuous changes in response to the disease were observed during the monitoring period.

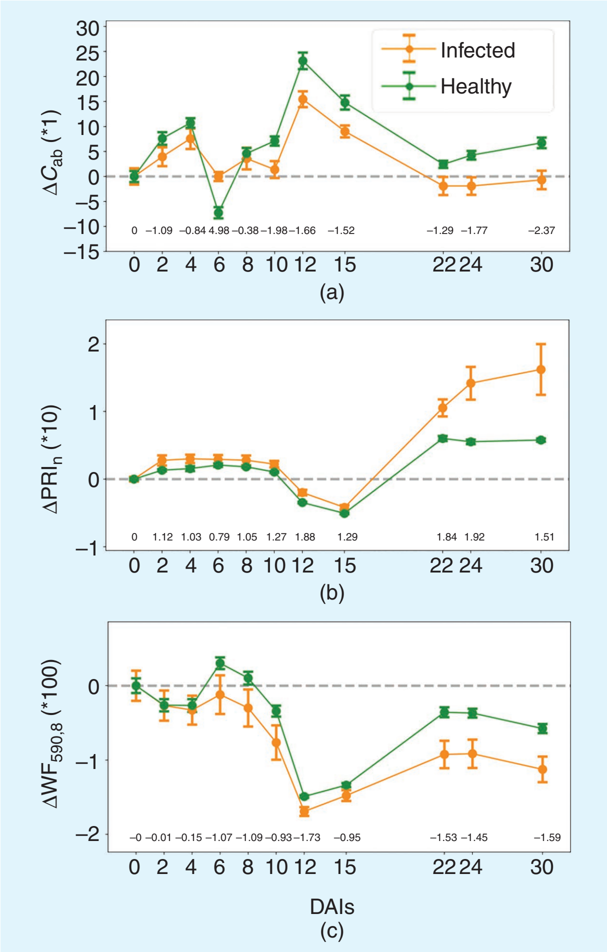

FIGURE 3. (a)–(c) Changes of sensitive hyperspectral features in infected ($n = 72$ samples) and healthy areas ($n = 72$ samples) on different days after infection (DAIs). The error bars represent the 95% confidence interval, and the values included represent the effect size, as determined by Cohen's d.

VIs responded to the disease by DAI 8, with the PRI_n, related to xanthophyll and photosynthetic efficiency, showing continuous changes until DAI 30 [Figure 3(b)]. PRI_n remained close to zero in healthy areas at DAI 0 but sharply increased in infected areas after DAI 15. WFs, particularly $WF_{586,6}$, $WF_{590,7}$, and $WF_{590–598,8}$ (located within the yellow edge region, 550–650 nm), exhibited the earliest response at DAI 6. Changes in $WF_{590,8}$ in infected areas consistently preceded those in healthy areas. Although WFs responded rapidly to disease onset, the trends were noisy and discontinuous, particularly in the early stages of infection [Figure 3(c)], suggesting instability in the early stage.

ALGORITHMS FOR MONITORING MAIZE LEAF SPOT

We evaluated three modeling techniques for monitoring maize leaf spot from UAV-collected data across four disease stages: early, mild, moderate, and severe. At each stage, we used leaf spot sensitive features selected in case study A to regress the maize leaf spot disease index. The modeling approaches include 1) two ML-based methods, including gradient-boosting DT (GBDT) and attention-based gated recurrent unit (GRU) neural networks (GRU-attention model), and 2) a physically based method—the process-guided DL (PGDL) approach, which uses a GRU-attention model pretrained on simulations and applies it to field data using transfer learning. The RTM simulations were produced by the Large-scale Remote Sensing Data and Image Simulation Framework (LESS) [140]. The leaf spectra inputs of the LESS were measured leaf spectra of diseased leaves with varying lesion coverage. The other inputs, such as plant spacing, sun zenith, and sun azimuth, were based on observations from Xinxiang, China, on 1 August 2021 between 11 a.m. and 2 p.m., in alignment with local agricultural practices.

The result showed that all models performed worse in the early disease stage; the PGDL approach demonstrated superior and more stable accuracy in that stage (Figure 4). The best performance was achieved with PGDL ($R^2 = 0.85$ in 2021, $R^2 = 0.93$ in 2023). The lowest root mean-square error (RMSE) was observed with PGDL (RMSE = 0.08 in 2021, RMSE = 0.06 in 2023), indicating that prior knowledge combined with measured leaf spectra significantly enhanced maize leaf spot monitoring accuracy.

CHALLENGES AND FUTURE PERSPECTIVES

LITERATURE REVIEW

The primary goals of this systematic review were to understand the advances in monitoring crop disease using hyperspectral remote sensing and to analyze the research challenges and trends. We adopted the method of gathering literature proposed by Cronin et al. [141] to obtain all relevant studies. First, the keyword combination "remote sensing & hyperspect* & (crop disease OR biotic) & (agriculture OR crops)" was used to search for studies in the Web of Science database published before 31 July 2024. This processing yielded a large pool of records. The identification step involved an initial check to remove duplicates and exclude records that were not peer reviewed as irrelevant (e.g., conference proceedings or reports). After examining the titles and abstracts, we excluded review studies and records that focused on topics other than crop disease. As a result, a total of 192 studies were involved in our dataset. Finally, we carefully read and analyzed these studies and categorized them based on research methods and application scenarios, aiming to gain insights into the progress and challenges in hyperspectral monitoring of crop disease.

CURRENT STATUS AND FOCUS

The number of studies monitoring crop disease using hyperspectral techniques increased sharply from 2006 to 2024 [Figure 5(b)]. Most publications were from the United States, followed by China, France, Australia, India, Spain, and Italy [Figure 5(a)]. Figure 5(c) highlights the most frequently studied crops, diseases, and hyperspectral features. The crops most commonly studied are wheat, rice, olive, potato, and oil palm. The most commonly researched diseases included blight, rust (specifically stripe and yellow rusts), mildew (both powdery and downy mildews), rot (stem and root rots), and various spot diseases (such as target, bacterial, and leaf spots). Among these, blights, including *Fusarium* head blight, fire blight, leaf blight, and late blight, were extensively studied. Research on hyperspectral features primarily focused on spectral characteristics, with growing attention on pigment concentration and SIF.

KEYWORD TRENDS ANALYSIS

"BURSTINESS" ANALYSIS OF KEYWORDS

The burstiness analysis in CiteSpace [142] was used to identify the 10 most prominent keywords in monitoring crop disease using hyperspectral remote sensing for 2006–2024. The burstiness analysis allows evaluating the frequently cited keywords and their significant periods. The burst strength in CiteSpace characterizes these keywords, with higher burst strength indicating a greater frequency of citation over a specific period. A burst means a sudden surge in the frequency of a particular keyword. We adopted a broad perspective, incorporating all the keywords from the titles, abstracts, keywords provided by the authors, and keywords extracted from the titles of the references cited (Figure 6).

The most prominent keyword (based on strength) in 2020 was ML, followed by DL, bacterial wilt, and yellow rust. The research foci can be broadly categorized into two periods, based on evolving research trends and keyword bursts: from 2006 to 2012, focused on equipment, algorithms, and applications, and from 2012 to the present, with an increased focus on advanced algorithms like

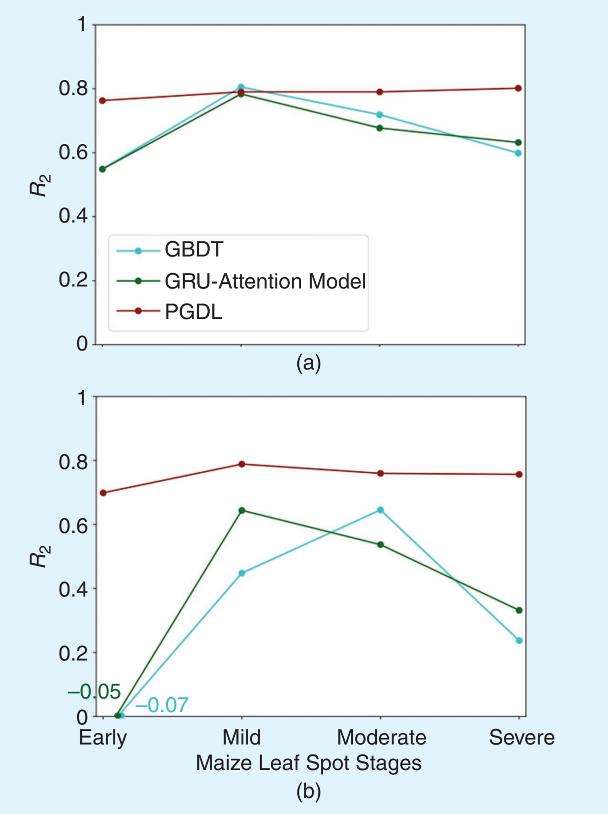

FIGURE 4. Model performance for monitoring maize leaf spot across different disease stages. Methods include two ML-based methods—gradient boosting decision tree (GBDT) and GRU neural network with attention mechanism (GRU-attention model)—and one physically based method, the process-guided DL approach (PGDL). (a) 2021. (b) 2023.

ML and specific disease applications. For equipment, the burst of handheld radiometry began in 2006 and gradually weakened after 2012 due to the development of imaging hyperspectral technology and other platforms, such as drones and airborne platforms. For algorithms, researchers constructed disease index models for simulating diseases before 2012. For applications, sugar beet was a focal research species.

The research foci from 2012 to the present have focused on algorithms and applications. For algorithms, the burst intensity of ML and DL remained high due to the rapid development of advanced artificial intelligence technologies. More remote sensing features were simultaneously used to monitor disease, such as the wage index and the LAI. For applications, yellow rust and bacterial wilt received considerable attention. Drought stress has been continuously monitored since 2006 with weak intensity, but distinguishing between drought stress and disease has remained a research challenge.

A TIME ZONE OF KEYWORDS

We analyzed temporal zones, using CiteSpace to research deeper into the evolving landscape of research foci in monitoring disease using hyperspectral remote sensing for 2006–2024 (Figure 7). Please note that we included only keywords from titles and those provided by the authors to represent the evolution of our research topic better. While this approach limits the analysis to keywords found in titles and abstracts, which may exclude some relevant terms not explicitly mentioned by the authors, we believe that it provides a focused view of the main research trends.

The keywords can be divided into six categories: type of disease; species; features; algorithms; aspects of sensors, platforms, and scales; and an "others" category. The "others" category includes broad keywords that cannot be allocated to the previously mentioned five categories, such as remote sensing, disease, and biological stress.

The UAV has frequently appeared in the category containing "sensors, platforms, and scales" since 2020, and the multimodal fusion technology of hyperspectral and thermal IR sensors attracted attention in 2022. ML and artificial intelligence in the algorithm category are consistent with the results of keyword burstiness analysis. Spectral features in the "features" category, such as reflectance, VI, and wavelet transform-based features, were the main terms identified. Biochemical-parameter features (e.g., nitrogen and anthocyanin concentrations) and physiological parameters (e.g., fluorescence) were also mentioned.

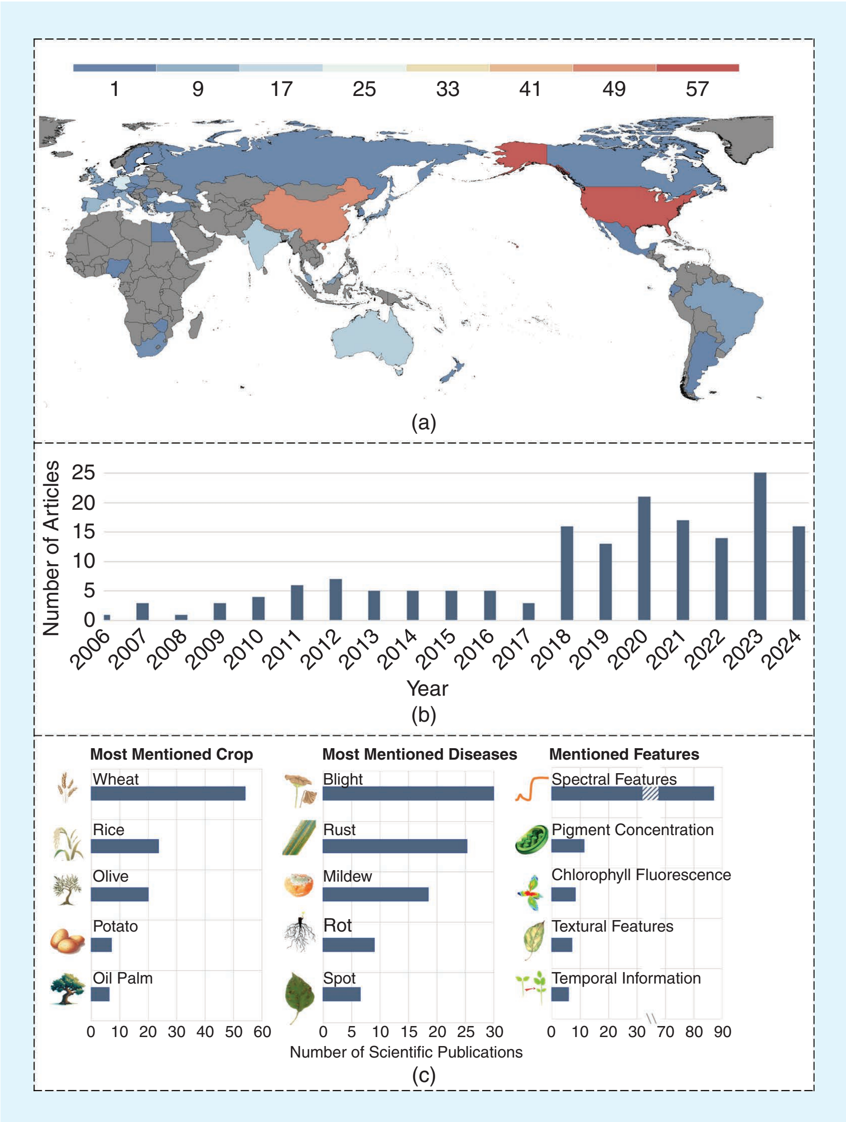

FIGURE 5. The status of global monitoring of crop disease using hyperspectral remote sensing. (a) The distribution of related publications around the world. Gray indicates no publications from the country. (b) The number of articles on the monitoring of disease using hyperspectral data from 2004 to 2022. (c) A summary of crops, types of disease, and hyperspectral-based features for 2006–2024.

FUTURE PERSPECTIVES

Based on the research presented previously, we can identify emerging trends and future research directions in hyperspectral remote sensing for monitoring crop disease.

The main challenges and trends have been illustrated in Figure 8.

Relationship between foliar and canopy scales: Observation platforms have shifted over time from handheld devices to airborne platforms, including piloted aircraft and drones, and the scale of observation has expanded from individual leaves to crops and even entire ecosystems. Foliar scale can have direct disease information, while canopy remote sensing is affected by canopy structure, soil background, and sun-observer geometry. These complexities often lead to a loss of accuracy when extrapolating results from foliar-scale analyses to the canopy scale [143]. To address this issue, future research should explore the factors causing the disconnect between canopy and foliar remote sensing. This includes examining structural and angular dependencies that might influence the data, potentially with the physically based RTMs. By understanding the invariants and establishing a more seamless link between leaf-level and canopy-level information, the robustness and ca-

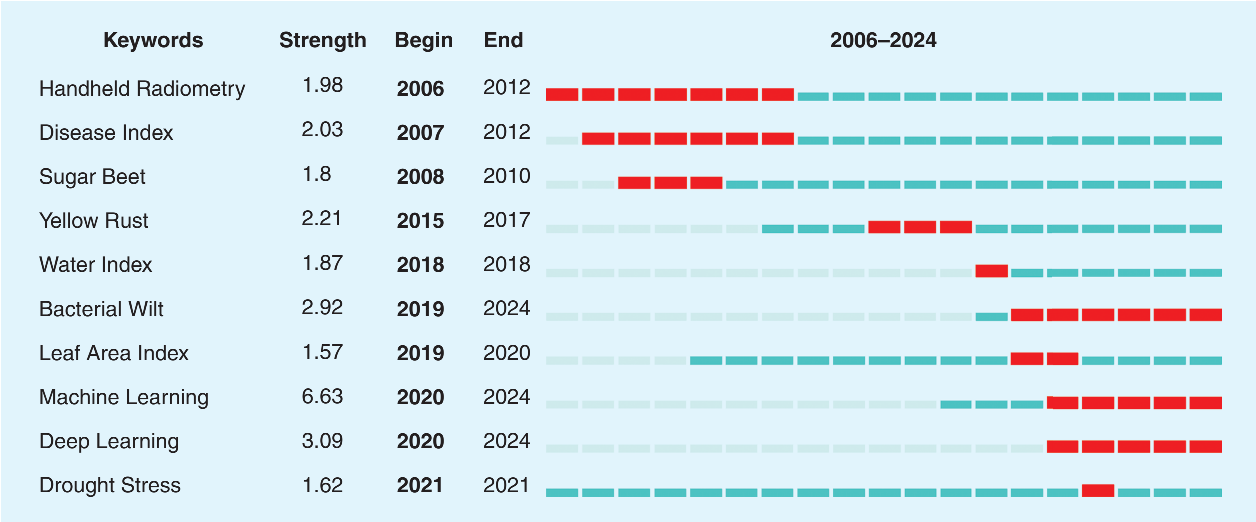

FIGURE 6. Top 10 keywords with the strongest citation bursts of hyperspectral remote sensing for crop disease monitoring. Each colored square represents a year. The red, cyan, and light cyan indicate years of the keyword significant citation bursts, appeared, and did not actively appear, respectively.

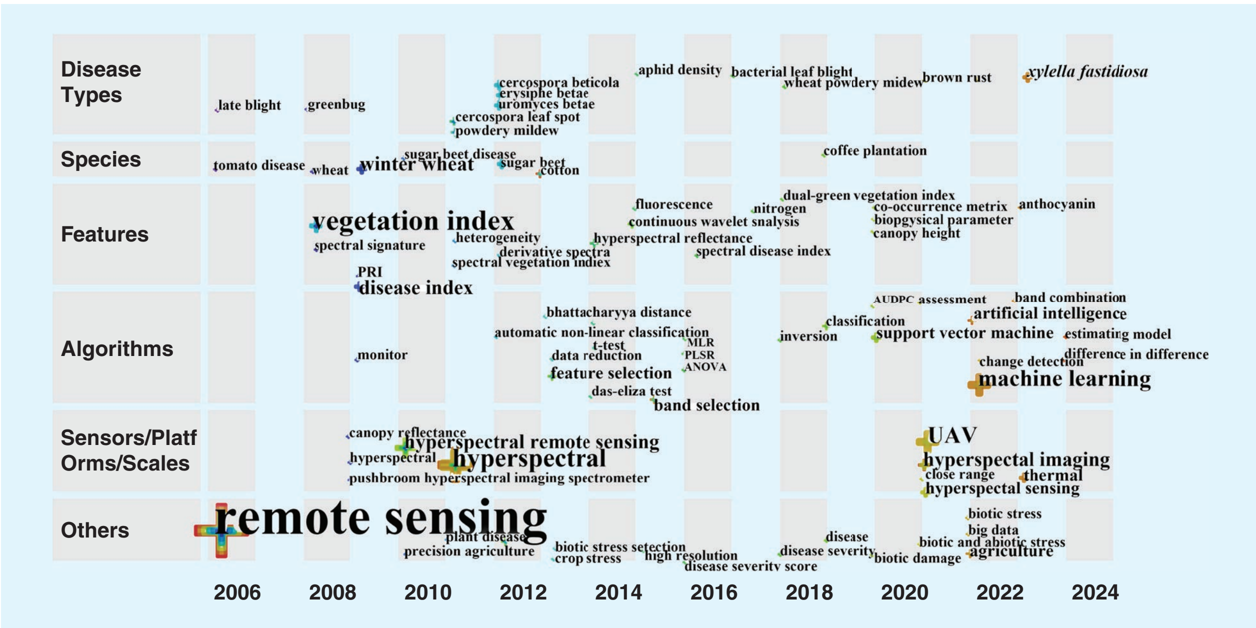

FIGURE 7. Keyword time zone view. A cross represents each keyword, and the vertical position of the keyword's first letter corresponds to the year of its first appearance. Arms around the crosses depict subsequent years, with the thickness of each arm indicating the keyword's frequency for that year. MLR: multinomial logistic regression; ANOVA: analysis of variance; AUDPC: area under disease progress curve.

pability of remote sensing algorithms can be improved. Additionally, the development of advanced hyperspectral sensors with higher spatial and spectral resolutions could bridge the gap between foliar and canopy scales. These sensors would enable more precise measurements at both scales, facilitating better integration of data and improving the accuracy of disease detection models.

Soil, crop structure, and phenology effects: Remote sensing captures a wide range of surface information, encompassing vegetation, diseases, and elements like soil, crop structure, and phenology [121]. For instance, the spectral response curves of soil and crop lesions can easily overlap, particularly in the VIS spectra [Figure 1(b)]. This overlap necessitates careful data preprocessing, including soil segmentation, before developing any monitoring models. Furthermore, selecting or developing spectral features minimally affected by soil background variations is crucial.

The crop structure, specifically in the canopy scale, can significantly impact spectral responses. This effect is most evident in metrics like the LAI and vegetation cover fraction. For instance, in dense canopies (LAI > 4), studies have suggested that structural variations have less influence on PRI, although this effect may vary across different crops and environmental conditions [143]. Therefore, choosing the appropriate temporal window for data collection can mitigate the influence of such structural disparities. Additionally, multiangle remote sensing can provide accurate information on crop structure [144]. Integrating multiangle hyperspectral images with advanced data fusion techniques could further reduce the impact of structural variations, enabling more accurate disease detection across different crop types and growth stages.

Phenological changes, such as leaf senescence, can also mimic the spectral features of disease [145]. There is an emerging need to transition from general group-wise comparisons to more sensitive methods capable of detecting deviations in individual diseases. One promising approach is to employ time-series analysis of hyperspectral data, such as DL-based anomaly detection and change point analysis. This could differentiate between typical seasonal changes and disease-related anomalies, enabling early disease detection at the individual level. Similar to phenology, certain physiological and biochemical characteristics of crops indeed exhibit significant daily cyclical changes [146]. For example, influenced by the light cycle, photosynthesis, stomatal opening and closing, and chlorophyll synthesis and degradation show daily cyclical changes. Therefore, considering the timing of data collection and crop growth characteristics is very important for remote sensing disease monitoring.

Lack of sensitive and robust features: Traditional ML has remained the most used approach for hyperspectral disease monitoring in recent years. One of the key challenges in building traditional ML models is identifying appropriate input features [147]. Researchers typically

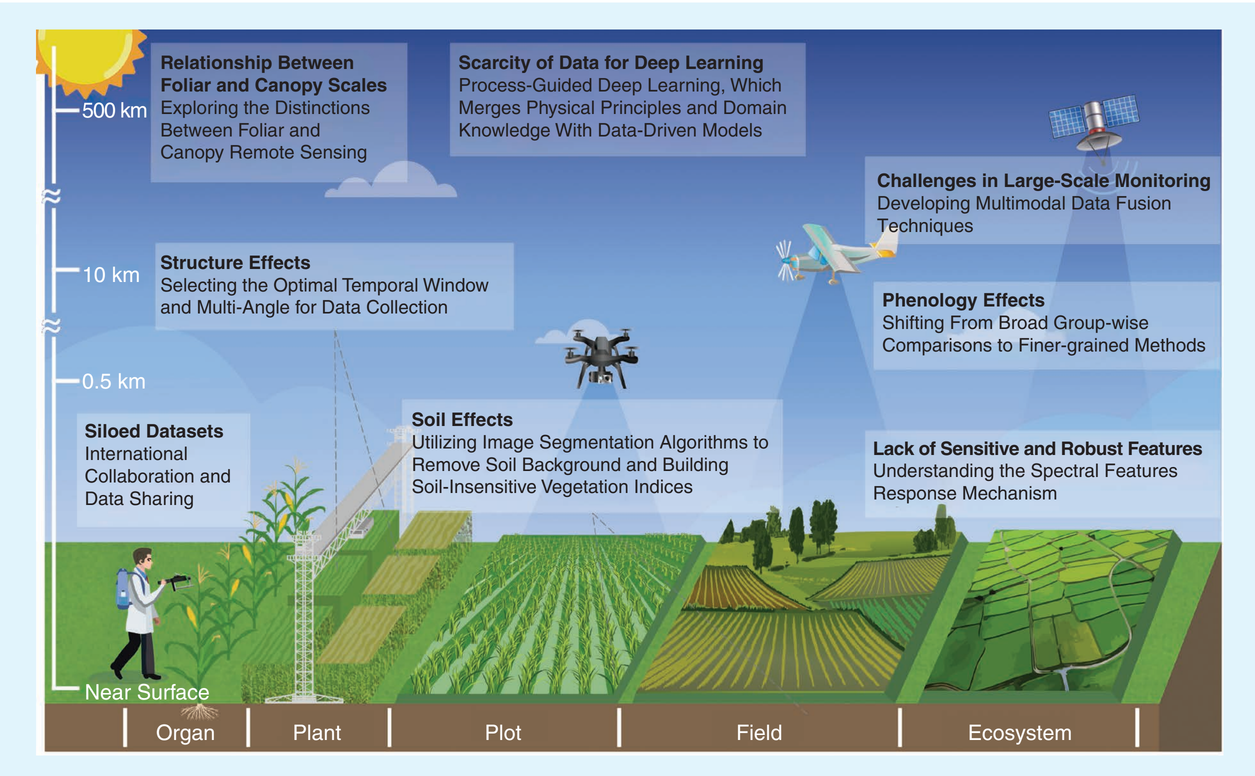

FIGURE 8. A summary of challenges and trends. Key uncertainties arise from soil/background, crop structural and phenological, and atmospheric effects as well as limitations in data availability and quality.

rely on their expertise to select spectral, textural, structural, thermal, pigment, and SIF features. However, the way these features respond to disease remains largely unclear. Understanding the feature response mechanisms and identifying features with high sensitivity and robustness are crucial for advancing future model development and improving monitoring accuracy. Therefore, rigorous controlled experiments at both leaf and canopy scales are necessary.

Challenges in large-scale monitoring: Several hyperspectral satellite missions focused on vegetation monitoring are currently underway. These missions, which provide rich spectral information, hold significant potential for monitoring large-scale crop disease. However, spatial and temporal resolution remain key limitations for large-scale applications. To make hyperspectral data suitable for agricultural applications, additional downscaling techniques are required. For example, multispectral satellites offer higher spatial resolution, while UAV platforms provide greater flexibility, particularly in terms of revisit frequency. Furthermore, the integration of ancillary data, such as climate information (such as temperature, humidity, and precipitation), can significantly influence the occurrence, spread, and severity of crop disease. Overall, the use of multimodal data fusion techniques can enhance the accuracy and effectiveness of crop disease monitoring at larger scales.

Scarcity of data for DL: Although DL has significant potential for hyperspectral disease monitoring, its application has been limited due to small and imbalanced datasets [148]. To address this issue, a new paradigm called "PGDL" has emerged [149]. PGDL integrates domain-specific knowledge and physical models into DL approaches, which could help overcome challenges in hyperspectral disease monitoring, such as the difficulty of solving inverse problems or modeling complex physical processes. This approach has been evaluated for quantifying the biomass and nitrogen concentration of cover crops from hyperspectral remotely sensed imagery [81]. PGDL, however, has rarely been tested in remote sensing for monitoring disease because disease cannot be directly inferred using RTMs. Two potential solutions could resolve this issue: first, from a mechanistic perspective, developing RTMs that consider disease parameters, and second, from an empirical perspective, using measured foliar spectral information for disease with different severities to simulate canopy data using canopy RTMs. In summary, combining RTMs with DL is a promising solution for exploring hyperspectral data for crop disease, as demonstrated in recent publications [39], [50], [150]. However, the way to combine RTMs with DL requires further exploration and research.

Siloed datasets: In contrast to digital red, green, and blue (RGB) images for classification, hyperspectral data for disease monitoring are costly due to the specialized equipment required and the time-intensive nature of fieldwork and data processing. This, in turn, hinders the transferability and validation of monitoring algorithms. A comprehensive study that includes different scales, regions, and diseases requires collaboration among international researchers. For example, the rice blast index (RIBI) development relied on a vast dataset of foliar- and canopy-scale reflectance spectra and satellite imagery gathered over seven independent campaigns in four years [151]. The specificity of RIBI was assessed using independent hyperspectral datasets containing healthy leaves and leaves infected with sugar beet rust, powdery mildew, and *Cercospora* leaf spot [9]. Sharing datasets of crop disease plays a crucial role in evaluating model transferability by providing a standardized benchmark for fair comparisons. Furthermore, we should develop standardized data formats and metadata protocols for hyperspectral data. The standardizations will effectively help the sharing and integration of datasets across different research groups and institutions.

Overall, hyperspectral remote sensing holds significant potential for monitoring crop disease across a range of scales, from individual organs [152] to entire ecosystems [78]. However, practical implementation in real-world agricultural settings remains a critical consideration. This involves assessing the cost-effectiveness and operational feasibility of these methods [125]. Moreover, integrating hyperspectral remote sensing with other agricultural management practices, such as precision agriculture, integrated pest management, and climate-smart agriculture, could enhance the sustainability and resilience of agricultural systems. By combining hyperspectral data with additional agronomic data sources, including soil health maps, weather forecasts, and crop growth models, farmers and agricultural advisors can make more informed decisions regarding disease management, resource allocation, and crop protection.

CONCLUSION

Effective and timely monitoring of crop disease is critical for field management, food security, crop breeding, and ultimately, improving final yield. Recent advancements in hyperspectral sensor technologies and data analysis techniques have provided powerful tools for monitoring crop disease at both high spatial and temporal resolutions. This review offers a comprehensive overview of the key aspects involved in hyperspectral remote sensing for crop disease monitoring. We began by defining common crop diseases and their symptoms, and then we explored hyperspectral-derived features used in crop disease monitoring. We also introduced four criteria for selecting relevant features. Additionally, we reviewed algorithms currently used in crop disease detection and highlighted their advantages and limitations. Furthermore, we highlighted five key application areas and presented two case studies to illustrate the potential of hyperspectral remote sensing. Finally, the future perspective of hyperspectral remote sensing for crop disease monitoring was discussed after an objective analysis of articles. Looking ahead, advancements in image processing, data analysis, and the development of sensors with subnanometer spectral resolution will greatly improve disease monitoring accuracy and scalability. The integration of hyperspectral data with other agricultural management practices, along with reductions in the cost of hyperspectral instruments, will further accelerate the adoption of these technologies. By overcoming current barriers, these innovations will lead to more effective and timely disease management and improved agricultural practices, ultimately supporting global food security and crop resilience.

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