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Hyperspectral remote sensing for discrimination for plant disease forecasting: Review

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Abstract
Forecasting plant disease is the process of predicting the severity of diseases affected by plants. Based on the environmental conditions, seasonal changes in nature, and weather conditions, the pathogen spread varies in plant diseases. Early forecasting gives farmers sufficient time to rearrange their crop schedules and protect the susceptible crop from severe infection by the pathogen. To prepare a forecasting system detailed observations over several years based on weather conditions may be necessary. Typically, pathogens tend to result in either loss of leaves or shoot area or changes in a leaf colour due to a reduction in photosynthetic activity. Remote sensing (RS) technologies provide a diagnostic tool that can serve as an early warning system, allowing the agricultural community to intervene early on to counter potential problems before they spread widely and negatively impact crop productivity. With the recent advancements in sensor technologies, data management and data analytics currently, several RS options are available to the agricultural community. By using RS data, the agricultural community can identify and quantify the health of agricultural systems, helping them to make management decisions that can increase farm profits while lowering agriculture-driven environmental problems.

Keywords: Remote sensing, hyperspectral sensing, spectrum data, disease identification

Introduction

Plants fights with many biotic stress factors like fungi, bacteria, viruses, nematodes and insects. These biotic stresses cause severe diseases and infections in agricultural crops and affect the productivity as well as yield gap. Assessment of disease symptoms and pest invasions is a difficult process. Biotic stress induced damage has been analyzed by personal inspection and quantification. It needs more number of manpower and skilled persons. It is time, money and energy consuming process. To overcome this issue, remote sensing is a best method to evaluate the damage with accurate data.

Remote sensing is a technology useful to detect damage in agricultural crops over a large area in a less period of time. Due to biotic stress, plants showed various symptoms like wilting, curling or stunned growth, chlorosis and necrosis etc., (Prabhakar *et al.*, 2011) [58]. Biotic and abiotic stress impacts in crop plants can be identified, detected and estimated through the hyper spectral remote sensing and their spectral signatures (Fitzgerald *et al*., 1999) [24]. Hyperspectral remote sensing is a narrow wave band, providing data about biophysical, biochemical characteristics of agricultural crops by characterize, mapping and quantifying the agricultural crops (Sahoo *et al*., 2015) [64]. Absorption spectrum of narrow bands are recorded based on the specific characteristics of crop plants such as physical structure, water content, biochemical parameters etc., (Haboudane, 2002, Champagne *et al*., 2003 and Strachan *et al*., 2002) [27, 16, 71].

Multispectral remote sensors are useful to identify the pest and disease damage. However, it could not distinctively recognize the damage caused by the stress (Fitagerald *et al*., 1999). Hyper spectral remote sensing provides the qualitative and quantitative details of plant spectrum based on the vegetative parameters. It increases the detection speed and detects the damage caused by the pest and diseases with accurate map (Kumar *et al*., 2002 and Apan *et al*., 2005) [34, 2]. In remote sensing, plants or vegetation absorbs light energy and convert to the reflectance spectrum. It gives the assumption data about stress induced damage correlate with photosynthesis and physical structure of the plant. For instance, in air borne diseases, information on the incidence of disease can be known in order to forecast about its severity and expected load of inoculum. For pathogens which are soil-borne, seed-borne and the degree of infection can be estimated in the laboratory. Hence there is a need for remote sensing techniques to forecast the plant diseases.

Remote sensing

Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and thus in contrast to on-site observation. In a sensor data fusion approach, an early detection of each pathogen was possible by discriminant analysis. To monitor the plants, remote sensing techniques are grouped into two such as imaging and non-imaging approach based on the sensors. RGB cameras, multispectral imaging, hyperspectral imaging, thermal imaging and fluorescence imaging are the imaging approaches used in detecting plant diseases. Fluorescence spectroscopy, VIS and IR spectroscopy belong to non-imaging approaches (Bhupathi and Sevugan, 2021) [10]. Mutka *et al*., 2015 has summarized the plant disease phenotyping in accelerating the crop varieties development. Hyperspectral dynamics presented by Wahabzada *et al.*, 2015 [75] to detect the diseases in barley leaves mapping with transport network using a linear time matrix factorization technique. Yu *et al*., 2018 [88] who pointed out that the hyperspectral narrowband of the red-edge in the near-infrared region, was identified as effective bands for disease discrimination in vegetation. Healthy green plants have high absorption in the visible having high reflectance of IR region except for green band by Nilsson *et al*., 1995 [53] and Barbedo *et al*., 2016 [5]. Radiometric calibration using a Red Edge camera mounted on a multirotor UAV in multispectral images is performed by Hossein Pourazar *et al*., 2019 [28] to detect and classify plant diseases. This calibration step converts the digital number into reflectance and generated uniform blocks in normalization. T-test and entropy distances are measured to discriminate against the unhealthy and healthy class of plants from the orthomosaic data of citrus orchard which produced insignificant precision.

Mrinal Singha *et al*., 2019 [69] performed a phenological-based classification strategy and textural features were evaluated on the dynamics of paddy rice and presented for MODIS and HJ-1A images. Li *et al*., 2020 [38] and Pantazi *et al*., 2016 [55] conducted remote sensing monitoring on wheat scab (WS) in the Yangtze-Huaihe river region. A remote sensing estimation model (Winter wheat Scab Remote sensing Estimating Model, WSREM) of WSI was established based on meteorological factors and spectral information, to conduct the remote sensing evaluation of WSI. Based on the region of interest, Paulina *et al*., 2019 [56] inspected the crop and barley crops which are greener in the earlier stage of growth. Normalized Difference Vegetation Index (NDVI) relates green biomass during spring growth, Green Difference Vegetation Index (GNDVI) indicating the chlorophyll content and Normalized Difference Red Edge (NDRE) indicates chlorophyll content; are the three vegetation indices applied to multispectral data. Xiaoxue *et al*., 2019 [80] constructed the knowledge graph of crop diseases and insect pests promoting the automation and intellectualization of the system. This knowledge graph is the semantic web that exposes the interrelationship between entities which is divided into a schema and data layer. Fernandes *et al*., 2011 [23] forecasted the plant diseases using a web-based approach. Knowledge representation, extraction, fusion, and reasoning are the methods introduced in its application. Crop conditions are assessed by Ennouri *et al*., 2019 [20] using remote sensing techniques. Nucleic acid and protein analysis are done in plant disease detection using DNA based and serological methods (Martinelli *et al*., 2015) [45]. To identify the pathogen infections at the asymptomatic stage, biophotonic sensors and remote sensing technologies were used. Leaf chlorophyll or *Cercospora beticola* disease was assessed by the HyperART system were given by Bergsträsser *et al*., 2015 [7] to map the leaf transmission, absorption and reflectance using the properties of Spatio-temporal dynamics. The metabolism of peach leaves affected by PLC is in many ways similar to that of immature sink leaves were described by Moscatello *et al*., 2017 [46]. That is photosynthetic function is reduced and the leaf imports rather than export sugars. Further, the content of both non-structural carbohydrates and enzymes involved in their metabolism is similar to that of the sink and not source leaves. The chlorophyll content is monitored to detect the diseased leaves (Yu *et al*., 2014) [89]. Late blight disease and early blight disease of the vegetation by using the *in-situ* spectroscopy of potato are detected by LGold *et al*., 2020 [35] and tomato leaves are detected by Xie *et al*., 2015 [81]. Using Sentinel-2 satellite images, Leaf Area Index (LAI), leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) estimated by vegetation indices (Clevers *et al*., 2017) [17].

Hyperspectral sensing method

Hyperspectral data is large, especially when multiple plants are imaged for several days. A scan of a single plant could easily be around a gigabyte in size. If the whole spectrum range is analyzed then the process will take considerably longer than several wavelengths to analyze. However, there is a lot of information contained in the data, which could be valuable. Although multi and hyperspectral images can potentially carry more information than normal photographs, they are usually captured by expensive and bulky sensors, while conventional cameras are ubiquitous and present in many consumer-level electronics stores. This has resulted in developing systems based on the visible range, which also leads to a more focused discussion. More information on multi and hyperspectral imaging applied to plant diseases can be found in Sankaran *et al*., 2010 [67]. Spatially reference time series of close-range hyperspectral images presented in Behmann *et al*., 2018 [6] to track the position of the symptoms automatically. Albetis *et al*., 2017 [1] identified from the Unmanned Aerial Vehicle (UAV) images (spectral bands, vegetation indices and biophysical parameters) using univariate and multivariate classification approaches in Flavescence doree, grapevine disease. MicaSense RedEdge sensor includes five independent high precision sensors to capture the vegetation response at five spectral bands (SB): blue, green, red, red-edge and near-infrared are acquired in UAV images. Pix4D software used to manage and process the UAV images. Univariate and multivariate approaches have been implemented in data acquisition, processing and analysis of spectral bands. Dash *et al*., 2017 [18] using the targeted application of herbicide. The physiological stress of trees is being monitored by manned aircraft. The crown and needle health representing density and discoloration respectively are assessed time series multi-spectral images of the forest captured. Red edge and near-infrared bands are helpful to detect the stress in plants at an earlier stage. High-resolution thermal and hyperspectral imagery is captured to predict the Verticillium wilt Calderón *et al*., 2015 [15] using remote sensing at an earlier stage. The classification methods, Linear discriminant analysis (LDA) and support vector machine (SVM) are applied to the images of hyperspectral generating the accuracy of 71.4% and 75% respectively finding the *Verticillium dahliae* affected in olive plants. This olive wilt is a disease is also assessed by using the RGB vegetation indexes measuring normalized green-red difference index

(NGRDI), Green Area (GA) and triangular greenness index (TGI) representing the inoculation effect.
Multi-scale image matching method Ze *et al*., 2019 [19] has been developed for producing a complete and accurate Amery ice shelf velocity field from Landsat 8 images. The relationship between the template size and the image entropy is investigated and the high contrast regions are distinguished preliminary operation improving the matching results over the regions. Hyperspectral reflectance and multi-spectral imaging techniques based on neural networks were used by Moshou *et al*., 2011 [48] and Golhani *et al*., 2018 [25] to detect the yellow rust plant disease in winter wheat. GPS has been integrated with a multi-sensor platform where calibration of the data processing unit is performed. Successive projections algorithm (SPA)- multiple linear regression (MLR) was applied in Li *et al*., 2017 [36] to construct spectral sensitive wavelengths of winter wheat for leaf area index (LAI). PCA loadings BPNN model Yao *et al*., 2019 [86] calculated the chlorophyll content to detect wheat stripe rust disease at early stage. Krezhova *et al*., 2014 [33] implemented DAS ELISA techniques to perform serological analysis on the tobacco plant leaves to detect the Bulgaria *Tomato spotted wilt virus* (TSWV) on the leaf. Randive *et al*., 2018 [60] implemented Non-destructive techniques using vegetation indices to identify various diseases on plants. The special signature, light reflectance changes, water content are analyzed using spectroscopic techniques. Maximum reflectance bands of chlorophyll are found to be related to vegetation nitrogen concentrations while comparing spectral reflectance data and ground observations Boegh *et al*., 2002 [11]. Based on the green leaf area index and nitrogen concentration, the spectral reflectance and vegetation indices are calculated.
Lu *et al*., 2018 [41] and Jones *et al*., 2010 [30] used a high-resolution portable spectral sensor to detect multi-diseased tomato leaves in different stages, including early or asymptomatic stages. The principal component analysis was conducted to evaluate Fifty-seven spectral vegetation indices (SVIs) to detect late blight, target, and bacterial spots in tomato leaves. UAV images are taken from RGB and CIR Canon IXUS/ELPH cameras to map the Acacia longifolia flowers present in the coastal and pine forest areas. Multispectral images with high resolution are captured using RGB cameras to determine the severity and NDVI of the rice sheath Zhang *et al*., 2018 [92, 93]. High-end multiSPEC 4C and S110 NIR camera were used by Nebiker *et al*., 2016 [51] to predict the grains and plant diseases with the use of lightweight multispectral UAV sensors.

Classification Using Spectrum Data

Classification approaches aim to divide the data into several distinct classes. They originate from a family of statistical or machine learning techniques Yang *et al*., 2017 [85]. One such approach is quadratic discriminant analysis (QDA), which classifies by using a covariance matrix, which compares classes. The QDA method was used in a study with Avocado plants, to examine the fungal disease Laurel wilt (*Raffaelea lauricola*), using plants located both in the field and glasshouse. It is possible of course to use alternative methods at each stage of the analysis pipeline. For example, rather than use QDA, a decision tree approach has been used and reached 95% accuracy Sankaran *et al.,* 2012 [65]. Choosing the correct approach for the data, as well as ensuring sufficient dataset size and quality are the key components. Such machine learning approaches represent an increasingly-common set of classification and prediction algorithms. Machine learning approaches train algorithms using a training dataset, intending to analyse and predict results from new unseen data. Deep Convolution Neural network model, VGG16 Wang *et al.,* 2017 [77] is used to detect the severity of plant disease from the apple rot images with an accuracy of 90.4%. VGG16, VGG19, Inception-v3, and ResNet50 are the fine-tuned four state of the art deep models trained to perform fine-grained classification where VGG16 shows high accuracy. Wallelign *et al*., 2018 [76] identified Soyabean plant disease using the CNN based LeNet Architecture and classified with an accuracy of 99.32% achieved from the plant village dataset images. Adaptive moment estimation (Adam) is used to train the model. Filtering the input image followed by applying max pooling, ReLu activation functions in the subsequent output layers, the output is given to the softmax layer to produce probability distribution by this model.
Sladojevic *et al*., 2016 [70]; Rahman *et al*., 2020 [59] used the deep learning-based approach, Convolution neural network to classify the rice plant disease and pest. Adopted VGG16 and Inception V3 to recognize diseases and CNN architecture of two-stage. Luo *et al*., 2008 [41] predicted crop diseases to warn pest Crop diseases are been identified automatically by using CNN. Boulent *et al*., 2019 [12] contributing more sustainable and secure food production. Object detection, which provides identification and location as a bounding box and segmentation, which provides identification for each pixel is performed to identify the disease of a plant. Vilasini *et al*., 2020 [74] discussed CNN based approaches for Indian leaf species identification from the white background using smartphones. Variations of CNN models over features like traditional shape, texture, colour and venation apart from the other miniature features of uniformity of edge patterns, leaf tip, margin, and other statistical features are explored for efficient leaf classification. Singh *et al*., 2019 [69] proposed an innovative model named as multilayer convolutional neural network (MCNN) for the classification of Mango leaves infected from the fungal disease named as Anthracnose. The higher performance of the proposed work is confirmed with an accuracy of 97.13% when compared with other state-of-the-art approaches for its accuracy. On applying many classification techniques to hyperspectral images, soft independent modeling of class analogy (SIMCA) proved as the strongest in discriminating healthy and unhealthy as non-symptomatic diseased (MS) leaves of peer and apple trees. Nikrooz *et al*., 2018 [52] before spreading fire blight disease, it is detected at an earlier stage by identifying modified triangular vegetation index and modified triangular vegetation index. Knowledge graph and case-based reasoning (CBR) has been used to detect the tobacco mosaic disease (Gu *et al.,* 2018) [26]. These techniques produced good results compared to PCA and SVM classifiers. Wavelet transformations analysis and SVM combined to forecast cucumber diseases by Wang *et al.*, 2018 [77] with an accuracy of 86%. Zhao *et al*., 2016 [94] also detected cucumber leaf spot diseases. Rule-based and frame-based knowledge representation expert systems. Fajri *et al*., 2017 [21] developed to detect many types of soybean diseases and proposed Certainty factors to detect disease of plant preventing pest with an accuracy of 90%. Lopez *et al*., 2016 [39] detected Red blotch diseases of almond trees by assessing chlorophyll, carotenoid pigment indices, and fluorescence at canopy and leaf level. Healthy and infectious trees are classified using a non-linear SVM technique. The canopy characteristics of maize crops are studied by Xie *et al*., 2016 [82]. The carotenoids and the vegetation indices can be estimated using Partial Least Square

Regression PLSR Yi *et al*., 2014 [87] which are expressed as mass per unit surface area or leaf area.

Applications of remote sensing in disease identification

Rumpf *et al*., 2010 [62] used the same dataset as Mahlein but with different analysis approaches; decision trees (DT), artificial neural networks (ANN) and support vector machine (SVM). All approaches require prior knowledge, however once trained have proven to be efficient. For example, with *Cerospora* leaf spot the accuracy for SVM is 97% (compared to DT 95% and ANN 96%); for Sugar beet rust the accuracy is 93% (DT 92%, ANN 95%); and for Powdery mildew the accuracy is 93% (DT 86%, ANN 91%). Measuring the severity with leaf area coverage after the disease has covered 1-2% of the leaf the accuracy is 62-68% and for more than 10% leaf coverage the accuracy is almost 100%. This demonstrates that it is possible to use a variety of analysis methods on the same set of hyperspectral data to elucidate different insights and achieve different levels of accuracy choice of technique is important. Mahlein *et al*., 2012 [43] analyzed sugar beet diseases specifically *Cerospora* leaf spot, powdery mildew, and leaf rust. The range is 400-1000 nm with 2.8 nm spectral resolution and 0.19 mm spatial resolution. The plants were analyzed over a while (> 20 days) to monitor the different stages of each disease and the leaves were classified as healthy or diseased. *Cerospora* leaf spot classification accuracy varied depending on the severity of the disease (89.01-98.90%), powdery mildew accuracy varied between 90.18 and 97.23%, and sugar beet rust reached 61.70%, with no classification before day 20 using SAM.

Nandris *et al*., 1985 [50] discussed root rotting fungi of rubber tree detection using remote sensing methods in the Ivory Coast. Cessna 172 airplane with Hasselblad 500 EL/M was used to collect visual pictures, processed and the trichromatic selection was performed. Beyyala and Beyyala, 2012 [8] detected bud rot and basal stem rot disease in Coconut (*Cocos nucifera* L), mosaic, and greening in citrus using image processing technology. Sabrol *et al*., (2015) [63] by analysing the size, shape and colour of the affected region. The immature green fruit of citrus is detected using the Grey Level co-occurrence Matrix (GLCM). Ding *et al*., 2018 [19] to extract features from hyperspectral images and three supervised classifiers resulting accuracies SVM-86%, logistic regression-79%, and random forest 75%. Kejian *et al*., 2019 [31] used polymerase chain reaction (PCR) to detect the HLB bacterium (Huanglongbing) Bove *et al*., 2007 [13] in each leaf of the citrus plant. This disease has also been detected using near IR spectral reflectance by Sankaran *et al*., (2013) [66] NDVI, Modified RedEdge Simple ratio (MSR) and Vogelmann red-edge index (VOG) indications. Yellow rust disease, caused by the fungus *Puccinia striiformis*, is a serious threat to wheat production and impacts the yield and quality of wheat Zheng *et al*., (2019) [95]. The timely detection of crop diseases at different growth stages Bajwa *et al*., (2017) [4] are critical to the effective management of the economy and agriculture. Moshou *et al*., (2004) [49], Bravo *et al*., (2003) [14] discriminated wheat infected by yellow rust from healthy wheat. It was concluded that red-edge wavelengths should be useful in reflectance studies of crop disease throughout the season. Used a quadratic discriminating model combined with the sensitive wavebands (at 543±10 nm, 630±10 nm, 750±10 nm, and 861±10 nm) for yellow rust discrimination with the coefficient of determination of 0.96. Self-Organizing Map (SOM) neural network was used by Moshou *et al*., (2005) [47], Zhang *et al*., (2018) [92, 93] to perform data fusion on the spectral wavelengths discriminated against with 94.5% of classification accuracy. RGB vegetation indexes widely used in plant phenotyping. Shakoor *et al*., (2017) [68] and in assessing abiotic stress, showed considerable resolution in detecting changes in plant color that could be attributed to the inoculation factor, especially notable in a context of a lack of wilting symptoms.

Cotton Diseases

Verticillium

Verticillium wilt disease is a major disease caused in cotton plant and it cause reduction in cotton yield (Pegg and Brady, 2002) [57]. *V. dahlia Kleb*, *Verticillium albo-atrum* are the causative agent for Verticillium wilt disease (Bhandari *et al.*, 2020) [9]. Early prediction and prevention can prevent the cotton loss. Traditional method of disease severity analysis is time and effort consuming method. Jin *et al.*, (2013) [29] studied the hyperspectral analysis of verticillium disease in cotton. Based on the symptoms and severity in leaf, spectral reflectance bands spread in several spectrums. It showed that disease affected leaves reflected in spectrum.

Root Rot disease

Root rot disease is caused by *Phymatotrichopsis omnivora.* In U.S it was called as Texas root rot disease (Wang *et al*., 2020) [78]. It averts uptake of nutrients and water from the soil and kills the plant by starvation. And it spreads within the field through root contact. Diseased field areas are usually circular in shape with symptomatic death plants (Yang *et al.*, 2014) [84]. Later growth stage of the cotton plant highly affected with this root rot disease especially during August to September. For long ago, remote sensing has been used as beneficial mapping system for identifying cotton root rot in cotton fields (Taubenhaus *et al.*, 1929; Nixon *et al.*, 1975) [72, 54]. Due to large numbers of infected areas and their irregular shapes, remote sensing is a best and effective method for identification. Cotton root rot infection mapped by airborne image at the end of the season (Yang *et al.*, 2005) [83] and the various stages of infection during growing season also monitored (Yang *et al.*, 2014) [84]. Both the studies, ISODATA (Iterative Self-Organizing Data Analysis) with unsupervised multispectral imagery were used to identify Cotton root rot disease. Root rot infected and non-infected zones were classified based on the spectral classes. Multispectral and hyper spectral remote sensing is effectively differentiating the diseased infested fields. As unmanned aerial vehicles (UAVs) was introduced into agricultural remote sensing. At single plant level, cotton root rot disease was identified by UAV remote sensing. With the help of UAV, high resolution of infected plant image was possible (Wang *et al.*, 2020) [78].

Duggar (*Phymatotrihopsis omnivore*) is fungal pathogen causing tremendous economic loss in cotton plant (Kenerley and Jeger, 1990) [32]. It was monitored by remote sensing by sudden death of the plant. Toler *et al.*, (1981) [73] also detected and determined the loss due to root rot in cotton fields caused by *Phymatotrichum*. Falkenberg *et al.*, (2007) [22] detected biotic stress root rot disease with the IR camera. In this study, he compared the early season IR image with late season digital aerial images. So that the IR camera was able to detect root rot disease affected areas.

Ramularia blight

The potential of three-band multispectral imagery from a multi-rotor UAV platform for the detection of Ramularia blight from different flight heights was evaluated. Increasing infection levels lead to the progressive degradation of the spectral vegetation signal, however, were not sufficient to differentiate finer-scaled disease severity levels. Findings such as that the separability and classification accuracies did not decrease up to a monitoring height of 500 m and that empirical, relative radiometric adjustment maintains multispectral DC signatures similar to flight heights with almost no atmospheric interference (100 m) have practical relevance. This means that the use of higher flight heights in property scale disease monitoring and precision farming can equilibrate the major limitation of multi-rotor mini UAV with respect to their restricted autonomy and coverage if compared to fixed-wing systems without bias foliar disease detection. Limited classification performances have motivated our ongoing efforts to apply a camera system with a higher spectral resolution (Micasense RedEdge M) and its combined use with a thermal imaging system FLIR 420T (FLIR Commercial Systems). Recent field campaigns include very low altitude imaging (<100 m) for the acquisition of improved spatial resolution imagery and multi temporal approaches for mapping Ramularia blight and other diseases in cotton (Xavier *et al*., 2019) [79].

Challenges and trends in monitoring plant disease

Despite the encouraging progress that has been achieved in the monitoring of plant diseases during the last few decades, some challenges still remain that hamper the implementation of the techniques in practice. Studies on seeking solutions to these challenges will shape future trends. The first issue lies in the detection of plant diseases at an early stage. Given the reliable RS monitoring of plant diseases are usually achieved when symptoms are fully exhibited, which may be too late for guiding the prevention. To improve the detectability of the diseases at an early stage, it is important to further exploit the feasibility of fluorescence, SAR, thermal and Lidar RS observations and fuse them with the well-developed VIS-NIR RS observations. Besides, it is worth attempting to use multi-angular remote sensing to increase the detecting capability to the lower canopy levels (Li *et al.,* 2015) [37]. The second issue is to accurately detect a specific disease under realistic field conditions where several crop stress may occur simultaneously. Currently, most monitoring studies or applications are conducted in experimental fields or areas with prior information, such as the type of diseases or other stresses occurred in the field (Mahlein *et al.,* 2013; Yuan *et al.,* 2014) [42, 90]. For an area that lacks corresponding information, it is challenging to achieve a reliable and accurate monitoring result. In the future, it is important to further explore the uniqueness of the features and transferability of the models. Some state-of-the-art algorithms, such as deep learning algorithms, may play an important role in this process. Besides, it is necessary to promote the establishment of a knowledge base about the background information about diseases or pests (i.e., geographical distribution, favorable habitats, soil types, climate conditions), along with a network of relevant ancillary data (e.g., meteorological data, soil data, and data from some wireless sensors networks). The prior information may help exclude many possibilities and thus lower uncertainty in the monitoring of plant diseases and pests under complicated scenarios. The third issue is to continuously track the dynamics of the diseases at a fine resolution. To achieve this, the RS systems should have sufficiently high resolution at all the spatial, spectral and temporal dimensions. Currently, not a single RS system is able to satisfy these requirements. Besides, bad weather is also a major obstacle to the continuous acquisition of optical images. To tackle this issue, it is important to explore the possibility of synergizing high resolution satellite images with unmanned aerial vehicle (UAV) images to construct a successive time-series RS data. Besides, the fusion between optical RS data and radar data is also worthy of attention. The fourth issue is data and information sharing. Considering distributions and epidemics of plant diseases and pests is a transnational process, multinational collaboration is important for both research and application. Presently, the lack of sufficient survey data is a bottleneck in the modeling for monitoring plant diseases and pests. Therefore, it is suggested to mobilize data collection during the cultivation processes. For example, farmers or extension officers should be mobilized to record the occurrence and severity of diseases and pests in their managed fields through a smart phone app. Then, it is critical that the pooled data be easily accessible to support efficient data mining and model training with sophisticated algorithms. Here we expect the setup of corresponding international projects and observation networks that allow experiments, data collection, modeling and ideas shared at a continental or global scale.

Concluding remarks

Monitoring diseases reliably, timely and efficiently over vast areas is very important for plant protection assessment and management. During the last a few decades, various RS techniques have been introduced for monitoring plant diseases and exhibited great potential for complementing conventional laborious inspection. In this review, we summarized the latest developments in corresponding RS systems, RS features, feature selection techniques, monitoring algorithms and models for conducting a comprehensive, effective monitoring of plant diseases. We expect that this review of state of art research achievements in remotely sensed monitoring of diseases can provoke new thoughts and promote the development of corresponding theories, techniques and methods both in academia and production practice.

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