Chapter

UAV Remote Sensing: An Innovative Tool for Detection and Management of Rice Diseases

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Abstract

Unmanned aerial vehicle (UAV) remote sensing is a new alternative to traditional diagnosis and detection of rice diseases by visual symptoms, providing quick, accurate and large coverage disease detection. UAV remote sensing offers an unprecedented spectral, spatial, and temporal resolution that can distinguish diseased plant tissue from healthy tissue based on the characteristics of disease symptoms. Research has been conducted on using RGB sensor, multispectral sensor, and hyperspectral sensor for successful detection and quantification of sheath blight (*Rhizoctonia solani*), using multispectral sensor to accurately detect narrow brown leaf spot (*Cercospora janseana*), and using infrared thermal sensor for detecting the occurrence of rice blast (*Magnaporthe oryzae*). UAV can also be used for aerial application, and UAV spraying has become a new means for control of rice sheath blight and other crop diseases in many countries, especially China and Japan. UAV spraying can operate at low altitudes and various speeds, making it suitable for situations where arial and ground applications are unavailable or infeasible and where precision applications are needed. Along with advances in digitalization and artificial intelligence for precision application across fertilizer, pest and crop management needs, this UAV technology will become a core tool in a farmer's precision equipment mix in the future.

Keywords: rice, UAV, drone, sensor, remote sensing, vegetation index, PCR, sheath blight, blast, narrow brown leaf spot, *Rhizoctonia solani*, *Magnaporthe oryzae*, *Cercospora janseana*, symptoms, fungicides, threshold for economical fungicide application

1. Introduction

Rice (*Oryza sativa* L.) is one of the three major food crops (rice, wheat, and maize) with worldwide production of 502 million tons, feeding more than half of the world's human population. China and the US rank 1st and 17th in worldwide rice production, producing 149 million and 7 million tons of rice in 2020, respectively [1]. Rice is one of major field crops in the US and is planted on 1.3 million hectares in Arkansas, California, Mississippi, Missouri, and Texas.

However, the occurrence of diseases poses a major threat to rice production. Numerous fungal, bacterial, viral, and nematode diseases occur in rice-growing regions, causing significant yield and quality losses annually [2]. Rice blast caused by *Magnaporthe oryzae* (formerly *M. grisea*) is the most important disease worldwide followed by sheath blight caused by *Rhizoctonia solani* AG1-1A. In the US rice, sheath blight is the number 1 disease, causing more economic loss than rice blast [3–5]. Sheath blight infects leaf sheaths, leaf blades, and even panicles, causing up to 44% yield loss and a significant reduction in milling quality [6]. Narrow brown leaf spot (NBLS), caused by *Cercospora janseana*, is another important disease with worldwide distributions [7]. NBLS, considered a minor disease historically, has become one of the most important rice diseases in the southern US, especially Texas and Louisiana with the humid, warm Gulf Coast climate. NBLS is more severe at late plantings and in the ratoon (second) crop. Ratooning is a practice following main crop harvest to maximize production returns in Texas and Louisiana where cropping season is long enough for 2nd crop harvest. NBLS attacks leaf, sheath, internode, panicle branch and glume tissues, causing characteristic linear brown lesions. NBLS can cause grain yield loss of up to 40% [7].

Rapid and accurate identification and detection of rice disease are the first essential step for effective management of these diseases. Diagnosis of diseases by their visual characteristic symptoms is the most common practice at present. However, this disease detection process is time consuming and labor-some. Accuracy of disease identification and detection is highly dependent on the knowledge and experience of the inspector. For example, to detect and monitor sheath blight, visual inspection should start at the panicle differentiation growth stage of rice by walking across the field in a zigzag pattern many times [8]. Many stops are needed to scout for the presence of the disease based on its symptoms in the lower portion of canopy. This process repeats weekly at the early stages and more frequently (biweekly) at the late stages or under conditions most favorable for sheath blight to develop until heading.

Unmanned aerial vehicle (UAV) remote sensing provides a new way to detect and monitor disease development. UAV remote sensing offers a quick, accurate, large area coverage, and low-cost tool for disease assessment. Remote sensing is the science and art of acquiring information about material objects from measurements made at a distance without coming in physical contact with the objectives [9]. Remote sensors can sense the changes in spectral reflectance that results from the changes of external biophysical and internal biochemical characteristics of plant tissue [10]. Spectral properties of vegetation are determined by plant tissue features, including pigment and moisture content of tissue, leaf area index, ratio of live and senesced tissue biomass, and spatial arrangement of cells and structures [11]. Changes in the spectral properties of vegetation occur in the three distinguished spectral domains of vegetation reflectance, invisible (VIS: 0.4 to 0.7 μm), near-infrared (NIR: 0.7 to 1.3 μm), and mid-infrared (mid-IR: 1.3 to 2.5 μm) [11]. Infected or diseased plants change their spectral properties of vegetation. A reduction in chlorophyll production in infected tissue results in less absorption of blue and red band visible light. These changes are reflected in all the three blue, green, and red bands. So, yellow or brown color is present in infected tissue image. In infected plants, NIR bands are not absorbed by mesophyll cells but by stressed and dead cells, resulting in the presence of dark tones in acquired image. Therefore, remote sensing can detect these changes in spectral reflection pattern in infected or diseased plant tissue. This is the basis for the application of remote sensing on plant disease detection and quantification. Various sensors, including digital RGB (Red, Green and Blue) sensor, multispectral sensor, hyperspectral sensor, fluorescence imaging, and infrared thermal sensors, have been widely utilized to characterize plant disease symptoms, detect different diseases, and even quantify severity of many plant diseases in the laboratory and field [12–14].

UAV can also be used as an aerial fungicide sprayer for disease control. UAV spraying can operate at low altitudes and various speeds, and apply with low volumes, making it suitable for situations where arial and ground applications are unavailable or infeasible and where precision applications are needed for more economically and environmentally effective control of diseases. With the development of UAV technology, the use of UAV for aerial fungicide application has become a new means for control of diseases in rice and other crops in recent years [15]. Considerable acreage of rice crops has been treated with UAV spraying in many countries, especially China and Japan [15–18]. In 2020, total treated areas of crops were over 450 million hectares in China [16]. In Japan, approximately 40% of rice acreage is treated with UAV spraying [17, 18].

This article reviews the recent advances in the research and use of UAV remote sensing for the detection and management of crop diseases, with a focus on sheath blight and NBLS, two important fungal diseases in rice. This review article covers disease symptoms, traditional disease detection methods, remote sensing for disease detection, and UAV used as a tool for disease management. Conclusion and prospects are also included at the end of this review article.

2. Disease symptoms

2.1 Sheath blight

Sheath blight is soilborne disease and the fungus can survive as sclerotia in soil for up to 2 years [19]. The disease starts with the contact of sclerotia with leaf sheaths at or just above the water line after the sclerotia float out of the soil with irrigation water. The sclerotia germinate and infect the leaf sheaths at the stages of later tillering to early reproduction. Initial symptoms develop on the leaf sheaths and are circular, oval or ellipsoid, water-soaked spots in greenish-gray color (**Figure 1A**). The lesions enlarge and coalesce forming bigger lesions with irregular outlines and grayish-white centers surrounded by dark brown borders (**Figure 1A** and **B**). As lesions coalesce on the sheaths, entire leaves eventually die. Lesions on the leaf blades are more irregular with dark green, brown or yellow-orange margins. The lesions can develop extensively and coalesce on partial or whole leaf blades, producing a rattlesnake skin pattern (**Figure 1C**). Sheath blight spreads in the field vertically and horizontally. The disease moves up the plants (**Figure 2**) and may infect the flag leaves and panicles (**Figures 1D** and **3A**) under severe conditions. The fungus spreads in the field by growing its runner hyphae from tiller to tiller, from leaf to leaf, and from plant to plant, resulting in a circular pattern of damage (**Figure 3A**). The fungus can spread into the culms from early sheath infections and weaken the infected culms, resulting in the lodging and collapse of tillers (**Figure 3B**). Diseased plants reduce grain filling, especially in the lower portion of the panicles. Losses in yield tend to be more severe with increased lodging [8].

Sclerotia, the survival structures of the fungus, form on the surfaces of some sheaths and leaf blades. The sclerotia are white (**Figure 1E**) when first formed, and then turn brown or dark brown (**Figure 1F**). The sclerotia fall off the plants and serve as primary inoculum the following season. Mycelia in infect plant debris can also service as primary inoculum. Sheath bight is considered a monocyclic disease since the pathogen infection cycle occurs only once during a cropping season. The fungus does not produce any asexual or sexual spores for repeated infections under the field conditions [20].

Figure 1.
Sheath blight lesions on the sheaths (A and B), leaf (C) and flag leaf (D), and white (E) and dark (F) sclerotia on the sheaths.

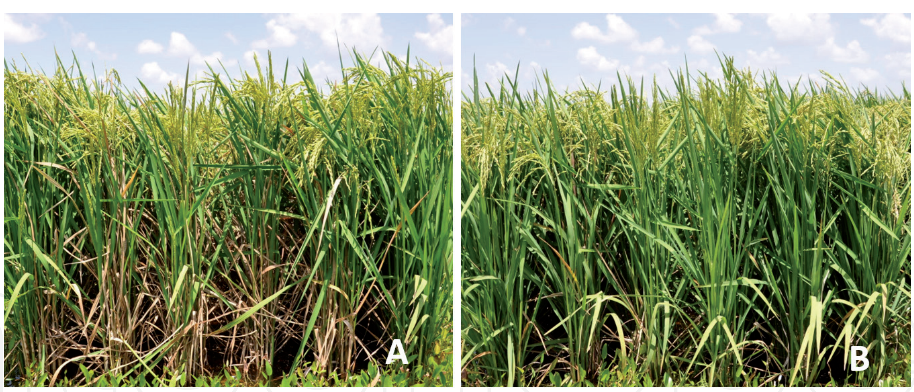

Figure 2.
Vertical development of sheath blight in pathogen-inoculated field plot (A) in comparison with healthy plants in non-inoculated field plot (B) at Eagle Lake, Texas, USA.

2.2 Narrow brown leaf spot (NBLS)

The NBLS fungus is seedborne and survives in infected seed and rice plant residue year after year, serving as primary inoculum. The fungus produces conidia, the structures for infection. Infection starts when the conidia germinate and penetrate host plant tissue through the stomata and grow intercellularly in the tissue [7]. The fungus attacks the leaves (**Figure 4A**), sheaths (**Figure 4B**), internodes, panicle branches and glumes (**Figure 4D**). On leaf blades, it causes short, linear, narrow, brown lesions parallel to the leaf veins (**Figure 4A**). Infection of the leaf sheaths results in a large, brown blotch or "net blotch" caused by the browning of the leaf

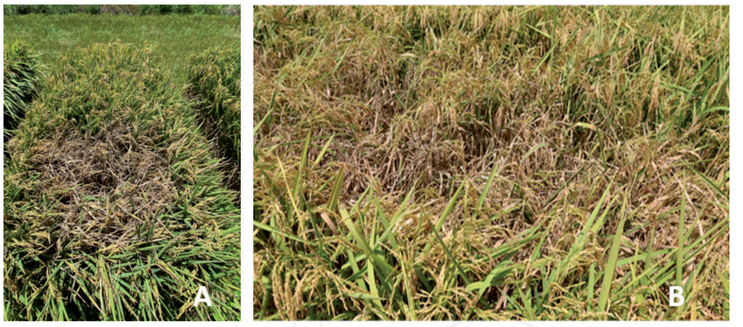

Figure 3.
Infected flag leaves and panicles in the circular infection area of field research plot (A), and lodging caused by sheath blight in a commercial rice field at Beaumont (B), Texas, USA.

Figure 4.
Narrow brown leaf spot (NBLS) lesions on the leaves (A) and sheath (B); NBLS net blotch symptoms on the sheath (C); NBLS lesions on panicle branches and glumes (D); and NBLS "neck blast" symptoms at the base of the panicle (E).

veins (**Figure 4C**). The fungus also can cause a "neck blight," where the internodal area above and below the node at the base of the panicle becomes light brown to tan (**Figure 4E**). The affected tissue area dies and the kernels in the lower portion of the panicle fail to fill (**Figure 4D**). As plants approach maturity, leaf spotting can become severe on susceptible cultivars and result in severe leaf blighting and premature death (**Figure 5**). The disease can cause premature ripening, yield reduction, and reduced milling quality. Low nitrogen levels increase the severity of the disease. The disease tends to be more severe at late plantings and in ratoon (second) crop. Ratooning is a common practice following main crop harvest in Texas and Louisiana to maximize the returns of rice production [21].

NBLS is a typical polycyclic foliar disease and infection occurs multiple times within a cropping season. The development of symptoms may take 7 days under conducive conditions (Zhou, unpublished data) to 30 days after infection [7].

Figure 5.
Severe narrow brown leaf spot (NBLS) and premature death in the field at Beaumont, Texas, USA.

The disease is airborne and spreads long distances by wind-borne spores, resulting in uniform distribution of the disease in the field [22].

3. Traditional disease detection

3.1 Sheath blight

Rapid and accurate identification and detection of sheath blight are critical for rice growers to employ a right measure such as fungicide application for control of this disease. Diagnosis of sheath blight by visual symptoms is the common practice to detect the presence of the disease. However, diagnosis based on symptoms is difficult since sheath blight may be confused with other sheath diseases with similar symptoms, such as sheath spot (also known bordered sheath spot) caused by *R. oryzae* and aggregate sheath spot caused by *R. oryzae-sativae*, especially at the early stages of disease development. Cooccurrence of these sheath blight-like diseases can be found in many rice production regions of Africa, Asia, North America, and South America [23, 24]. In the US, sheath blight, sheath spot, and aggregate sheath spot are commonly present in the field although sheath spot and aggregate sheath spot usually do not cause measurable yield loss in the southern US [8, 25, 26] whereas sheath blight and sheath spot do not cause yield loss in California [27]. Currently, sheath blight and aggregate sheath spot are the two key rice diseases in the southern states and California, respectively. To improve the accuracy of disease diagnosis, research has been conducted using polymerase chain reaction (PCR) technology for the detection of sheath blight. Matsumoto et al. [23] and Johanson et al. [28] developed PCR-based methods to distinguish these three pathogens. Sayler and Yang [29] developed a real-time PCR assay that can be used to detect and quantify the sheath blight pathogen in infected tissue at the early stages of infection. These molecular methods provide a new tool for the accurate detection of sheath blight in rice. However, this molecular approach has not been adopted for use in commercial rice production in Texas and other United States because of relatively high costs and inaccessibility of this technology to rice farmers. At present, the U.S. farmers still use the traditional diagnosis of sheath blight based on the characteristics of symptoms distinguishable from other diseases as described above.

Scouting for sheath blight and determining the need to trigger fungicide application are important for profitable production of rice. As other diseases, it is difficult to precisely estimate the potential levels of sheath blight in a field to make an assessment on the economic feasibility of applying a fungicide. However, given the high costs of fungicide applications and farmers' need to reduce production costs, the proper disease scouting and assessment is highly recommended. Damage caused by the disease depends on several factors that include cultivar susceptibility, disease pressure, weather conditions, plant density, and nitrogen fertilizers.

Sheath blight develops quickly under favorable environmental conditions. The following field scouting procedure is recommended for the rice farmers in Texas [8]. Detecting and monitoring the development of sheath blight should start scouting for the presence of sheath blight at the panicle differentiation growth stage of rice by walking across the field in a zigzag pattern (**Figure 6**). Farmer should periodically inspect rice plants above the water line for the early symptoms. If there is no sheath blight observed, the farmer should wait a week and monitor again; if some sheath blight is found, a more detailed monitoring procedure should be followed to accurately determine the severity of sheath blight. A large field should be divided into 45 to 50 acres (18 to 20 hectares) sections and inspection made in each section separately (**Figure 6**) to monitor more precisely. The farmer should walk the field sections in a "U" pattern and randomly stop to check for the presence of sheath blight. The stopping point is considered positive for sheath blight even if only one small sheath blight lesion is found on a single plant; the stopping point is considered negative if no sheath blight symptoms is observed. The total number of stops should be at least equivalent to the number of areas scouted (i.e. 50 acres (20 hectares) = 50 or more stops). To the end of the scouting, the percentage of positive sheath blight stopping points can be calculated by dividing the number of positive stops where sheath blight was found by the number of stops and multiplying by 100. Alternatively, the percentage of tillers infected can be calculated by dividing the number of tillers infected by the total number of tillers inspected and multiplying by 100. For the tiller infection assessment, the number of tillers with at least one sheath blight lesion and the total number of tillers inspected should be recorded in each stop.

The thresholds for economical fungicide application are based on the amount of sheath blight present and the susceptibility of the cultivar planted. With very susceptible and susceptible cultivars, 35% positive stops indicate that a fungicide is necessary; moderately susceptible cultivars require 50% positive stops to justify a fungicide application. Alternatively, with very susceptible and susceptible cultivars, 5 to 10% tillers infected indicate that spraying a fungicide is warranted; moderately susceptible cultivars require 10 to 15% tillers infected to justify a fungicide application.

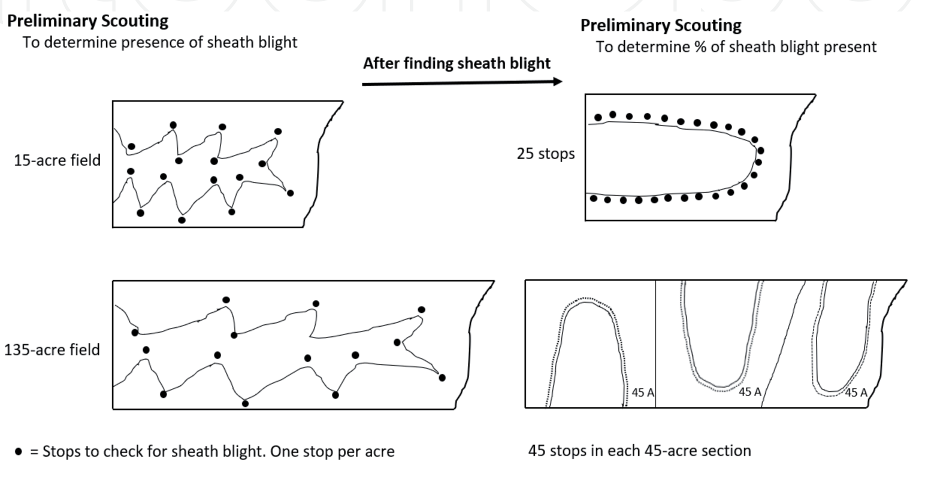

Figure 6.
Scouting procedure for sheath blight detection in the 15-, 45-, and 135-acre (6-, 18-, and 55-hectare) field (source: [8]). A = acre.

This scouting procedure should be repeated until the heading growth stage. However, if most conducive conditions are present and persistent at the growth stages after panicle differentiation, sheath blight should be scouted at the intervals of two times a week.

3.2 Narrow brown leaf spot (NBLS)

NBLS has its own characteristic symptoms that can be distinguished from other diseases in rice. This is especially true when the disease is at its late development stages. However, diagnosis of NBLS by visual symptoms may be confused with other diseases, including brown spot (caused by *Cochliobolus miyabeanus*), white leaf streak (*Mycovellosiella oryzae*), and leaf blast (*Magnaporthe oryzae*). This difficulty becomes more profound when these four diseases are at their initial stages with similar spot symptoms. Like NBLS, brown spot and rice blast, especially brown spot, are commonly present in rice. All rice cultivars, including hybrids, are susceptible to brown spot. Fortunately, white leaf streak is of not much concern for disease diagnosis since it has been reported only in Texas and Louisiana [30, 31] and in several other countries [32]. White leaf streak is a minor disease and is not commonly present in rice.

Scouting for NBLS and monitoring its development are relatively simple compared to sheath blight. NBLS spreads by air-borne spores and its distribution in the field is uniform, which contrasts with sheath blight that is soilborne and spreads in the field in an aggregated pattern. NBLS symptoms first appear on old leaves and then develop on the upper leaves. Rice plants are susceptible to NBLS at all growth stages but become more susceptible from panicle emergence to maturity. Due to relatively slow development of the disease, weekly scouting for NBLS is recommended and the scouting procedure should start at the boot stage until heading.

The thresholds for economical fungicide application have not been established for NBLS yet. However, determining the need to trigger a fungicide application is based on the susceptibility of the cultivar planted, its growth stage, and weather conditions. Significant differences in susceptibility among rice cultivars are present. Some cultivars, especially hybrids, with acceptable levels of resistance do not need a fungicide treatment. A fungicide application may be warranted under the most conducive environments, including combinations of very susceptible cultivars, early growth stages infected, favorable weather conditions and a consideration of ratoon cropping.

4. Remote sensing for disease detection

Remote sensing is an innovation to plant disease detection and monitoring since it provides rapid, accurate and objective observations and can be available real time and all the time. With remote sensing technology, we can rapidly and accurately observe and assess crop growth and disease development at large field scales and make it possible conduct multiple surveys and assessments within a short period of time. This is especially useful when surveying field crops such as rice to cover large field areas. The average size of field crops per farm in the US is relatively large and has continued increase. For example, average rice hectares per U. S. rice farm have been increased from 160 hectares in 2000 to 243 hectares in 2013 [33]. Using traditional field observations and ground surveys for crop diseases, such as rice sheath blight detection method described above, is a challenge to farmers since such visual inspection methods are time-consuming and labor-some. Such manual inspection is also subjective and random, and its accuracy is dependent on the knowledge and experience of the inspector.

4.1 Remote sensors

Various sensors, including digit (RGB) camera, multispectral camera, hyperspectral camera, infrared thermal imager, and fluorescence imaging, have been used in remote sensing for plant disease detection and monitoring [10, 12, 34]. RGB camera is one of the most used sensors because of its light weight, low cost, ease of operation, simple data processing, and low work environment requirements [34]. RBG camera can acquire grayscale or color images, which enables to detect diseased plant tissues with modifications in color, texture, and other spectral information. Hoverer, due to the limitation of fewer visible light bands, RGB camera might provide insufficient spectral information to accurately characterize symptoms and identify diseases. Vegetation features can be identified by extracting color indices from high-resolution images since each pixel value of image can be calculated from the reflectance or radiance of specific bands [34]. RGB camera has been used for the identification and detection of cotton bacterial angular (*Xanthomonas campestris*) and Ascochyta blight (*Ascochyta gossypii*) [35], grapefruit citrus canker (*X. axonopodis*) [36], and sugar beet Cercospora leaf spot (*C. beticola*) and rust (*Uromyces betae*) [37]. In rice, Zhang et al. [38] has successfully used RBG camera to detect and quantify sheath blight. Kurniawati et al. [39] used RGB images to achieve 95% of accuracy to diagnose rice blast, brown spot, and NBLS. Lu et al. [40] identified 10 rice diseases from RGB images using deep conventional neural networks (CNN) with an accuracy of 95%. These 10 rice diseases were rice blast, false smut (*Ustilaginoidea virens*), brown spot, bakanae (*Gibberella fujikuroi*), sheath blight, sheath rot, bacterial leaf blight (*X. oryzae pv. oryzae*), bacterial sheath rot (*Pseudomonas fuscovaginae*), seeding blight, and bacterial wilt.

Multispectral camera is the second most used sensor for plant disease detection. Multispectral sensors can sense and record the radiations from the visible and invisible portions of the electromagnetic spectrum. To the users, multispectral sensors are relatively inexpensive and have the advantages of fast frame imaging and high work efficiency. However, multispectral sensors have their limitations since they have low number of bands, discontinuous spectrum, and low spectral resolution [34]. Multispectral sensing has been used for the classification and detection of more than 16 fungal and bacterial diseases in over 11 field crops [12]. In rice, Zhang et al. [38] reported that multispectral sensor performed better in the detection of sheath blight in field plots compared to RGB sensor. Cai et al. [41] successfully used a multiple spectral sensor to detect and quantify NBLS in the field. Shi et al. [42] used PlanetScope multispectral imaging to classify and detect rice blast, dwarf virus, and glume blight (*Phyllosticta glumarum*) at a large field scale with an accuracy of 76%. Kobayashi et al. [43] evaluated the potential use of multispectral sensor for airborne detection of rice blast.

Hyperspectral sensing is another common method to diagnose and detect plant diseases. Hyperspectral sensors can sense and record a large number of very narrow bands and continuous spectra. They can provide more spectral band information and higher spectral resolution than multispectral sensors. Therefore, hyperspectral imagers have more capacity to capture spectral characteristics of symptoms and crops and to distinguish the differences in spectral traits between different crops [34]. The hyperspectral sensing approach has been used for the detection of more than 12 fungal, bacterial, and nematode diseases in 15 field crops [12]. In rice, sheath blight, rice blast and bacterial leaf blight can be identified with an accuracy of more than 93% using hyperspectral imaging data through machine leaning methods [44]. Most recently, Lin et al. [45] analyzed and compared the spectral responses to rice leaf and sheath tissue infected with sheath blight with healthy tissue and found that the hyperspectral sensing approach performed very well on the

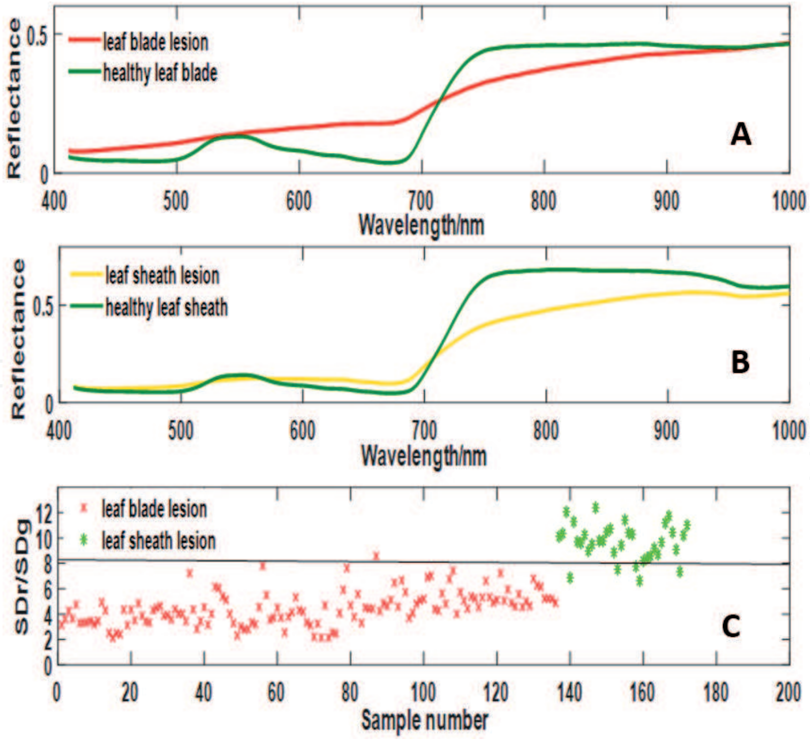

Figure 7.
Comparison of spectral curves of sheath blight-infected rice leaf blade (A) and leaf sheath (B) with their healthy tissues, and the ability of SDr/SDs to distinguish the leaf lesions from the leaf blade lesions (C) (source: [45]). SDr = red edge area; SDg = green peak area.

identification of sheath blight with an accuracy of more than 95%. Hyperspectral sensor could distinguish the spectral response curves of the diseased leaf blade (**Figure 7A**) and leaf sheath (**Figure 7B**) from their healthy tissues. Transformed data (SDr/SDg) could even distinguish the leaf blade lesions from the leaf sheath lesions (**Figure 7C**).

Infrared thermal sensors can detect radiation emitted in the thermal infrared range of 8 to 14 μm. They can be used to assess the surface temperature of leaves and plant canopies that are affected by water status [12]. Diseased plants and tissues usually suffer from water stress due to loss of healthy tissue, stomatal conductance, and photosynthesis, resulting in the changes in canopy temperature among different disease-related environments. Infrared thermal imaging has been used for the detection of more than six fungal and bacterial diseases in seven crops [10, 12]. Yamamoto et al. [46] reported the use of infrared thermal image to detect the occurrence of rice blast in Japan.

Using fluorescence technical approach for plant disease detection has not been widely studied as compared to other sensors described above. Fluorescence has been used for the detection of only several diseases, including wheat leaf rust [47] and citrus canker [48]. Fluorescence can assess the changes in photosystem II activity of plants under different levels of stress [12]. Infection causes chlorophyll degradation and reduced photosynthetic leaf area, resulting in the changes in the capacity of photosynthesis between diseased and healthy crops.

4.2 Remote sensing platforms

Satellite, airborne (aircraft), UAV, and ground are the most common platforms that have been used for the detection and monitoring of plant diseases. Applications of remote sensing on agriculture and disease detection and management are first studied and implemented using satellite and aircraft platforms equipped with remote sensors. For example, Colwell [49] conducted the first airborne imagery to monitor the occurrence of black stem rust of wheat and yellow dwarf of oat. Qin and Zhang [50] used Airborne Data Acquisition and Registration (ADAR) to detect and monitor the development of rice sheath blight with high accuracy for late development stages of the disease. Use of satellite image data has successfully detected and monitored rice diseases (sheath blight, blast, glume blight, and dwarf virus) [41, 51] and wheat diseases (powdery mildew and leaf rust) [52]. Ground-based sensors has also been used to detect crop diseases including fire blight of apple [53] and late blight of potato [54]. Satellite, airborne and ground-based remote sensing have been widely investigated and some of the developed techniques have been used for plant disease detection and management. However, most of the satellite and airborne remote sensing results and findings still remain in the research phases and wide implementations of theses remote sensing technologies for field crop disease detection and monitoring are limited due to their high costs of acquiring data, high technique demand for data processing, limited availability of needed and real-time data, and being inaccessible to end users (farmers). Ground-based remote sensing is difficult to meet the on-time detection of crop diseases at large scale farming setting for disease management. So far, these remote sensing technologies have not been used for the detection and monitoring of rice diseases in the US.

Recent advances in UAV remote sensing platform and data processing make it possible using remote sensor techniques to identify, detection and quantify plant diseases [12]. UAV-based remote sensing provides low costs, ease of use, high-resolution images, high efficiency, real-time inspection, and the ability to cover a large field scale. A study has been conducted by Garcia-Ruiz et al. [55] to compare the performance of UAV with a single engine fixed-wing aircraft using multispectral imaging sensor on the detection of citrus greening disease. The study found that UAV-based sensor provided 67 to 85% of identification accuracy whereas the accuracy was 61 to 74% with the aircraft-based sensor. The results of this comparative performance study demonstrate that UAV can be a low cost and reliable tool for crop disease detection.

Multi-rotors, helicopters, fixed wings, blimps, and flying wings are among the most UAVs used for crop phenotyping and disease detection [34]. Selection of UAVs is based on the purpose and budget of the research and implementation. Each UAV has its advantages and disadvantages in costs, flying ability (flying speed, altitude and duration), and payload capacity [34]. Multi-rotors are the most common used UAVs at present. Multi-rotor UAVs are low costs, can hover, and have low take-off and landing requirements. However, multi-rotor UAVs have their disadvantages of low payload, short flight duration, and being easy to be affected by weather conditions. Each UAV has a flight control system that can plan flight routes and setup flight parameters such as flight location, flight altitude, and flight speed.

UAV remote sensing provides an unprecedented spectral, spatial, and temporal resolution and an innovation tool for the detection of crop diseases [12, 56]. Investigations and reports on the use of UAV equipped with different sensors for field crop disease detection and monitoring have continued increase for the past five years [12]. In 2016 through 2019, there were at least 15 published research articles that involved more than 15 diseases in 12 field crops [12]. Sensors used in these studies include RGB sensor, multispectral sensor and infrared thermal sensor, and accuracy of disease identification and detection ranges from 0.64 to 0.97. These diseases studied are fire blight of apple [53], Ascochyta blight of chickpea [57], mistletoes of eucalyptus [58], myrtle rust of lemon myrtle [59], tar spot complex of maize [60], leaf spot of oilseed rape [61], myrtle rust of paperbark tea [62], late blight of potato [54], sheath blight [38] and NBLS of rice [41], needle blight of scots pine [63], gummy stem blight of watermelon [64], and leaf blotch, powdery mildew and yellow rust of wheat [65–67]. However, using UAV remote sensing for disease detection is still premature in comparison with research on the detection of crop drought stress [12]. Continuous research and further development on UAV remote sensing will make this innovation become a useful tool for farmers to detect and manage diseases. In this article, we focus on the development of UAV remote sensing for the detection and quantification of sheath blight and NBLS, two important rice diseases, as an example to demonstrate the usefulness of UAV remote sensing technology.

4.3 UAV remote sensing for sheath blight detection

A study was conducted in the field plots at Texas A&M AgriLife Research Center, Beaumont, TX, USA to evaluate the potential of using UAV remote sensing to detect and quantify sheath blight of rice [38]. A total of 67 rice cultivars and elite breeding lines with different levels of resistance to sheath blight were planted into plots of each consisting of seven 2.4-m rows, spaced 18 cm between rows. Each plot was divided into two equal-length sections, with one end section being inoculated with the sheath blight pathogen while the other end section left with no pathogen inoculation for the disease-free control. Ground truth sheath blight severity data were collected by visual assessment based on a scale of 0 to 9 where 0 represents no symptoms and 9 represents most severe in symptoms and damage.

Four-rotor Phantom 2 Vision+ UAV equipped with high resolution digit camera or multispectral camera was used to capture field plot images (**Figure 8**). The digit camera had 4384 x 3288 pixel resolution with three bands of red, green, and blue whereas the multispectral sensor Micansense RedEdge™ has five bands of blue, green, red, red edge, and near-infrared (**Figure 9**). The UAV flew at 27 m altitude to cover all 67 plots per image and 5.5 m to cover four plots per image, at a speed between 0 and 10 m/s depended on wind speed. Pix 4D was utilized to covert images automatically and Normalized Difference Vegetation Index (NDVI) and other vegetation indices of 67 plots were calculated and extracted by ArcGIS 9.1. Ground truth NDVI values of 67 plots were acquired by using GreenSeeker handheld crop sensor.

In this study, high-resolution 3-band RGB and 5-band multispectral images were analyzed to detect sheath blight-infected areas in the plots. Multispectral

Figure 8.
Four-rotor Phantom 2 Vision+ UAV equipped with a high-resolution digit RGB camera used in this study.

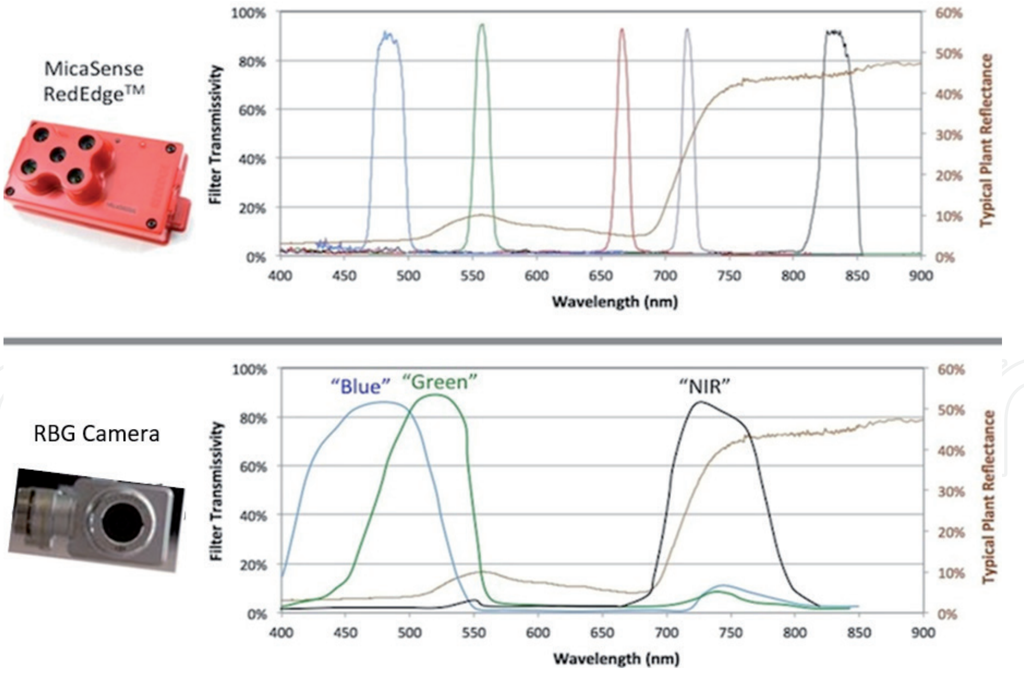

Figure 9.
Comparison of spectral responses of multispectral Micansense camera (upper) and digit RGB camera (lower) (source: [38]).

RBG image (**Figure 10B**) could more accurately reflect field environments such as green weeds, ground earth and plot shadow, and canopy characteristics including color, texture and structure information compared to original RGB image collected from digit camera (**Figure 10A**). Therefore, multispectral camera could provide more details than regular digit camera since the former has the narrow spectral band as shown in **Figure 9**. Transformation to HLS (hue, lightness, and saturation) (**Figure 10C**) from the false color image resulted in more apparent display of the sheath blight-infected areas with yellow to white in color in the plots. After NDVI values were calculated and the NDVIs map of 67 plots was developed (**Figure 10D**), it clearly showed the diseased areas were clearly differentiated from the healthy areas in each of the plots. The darker the image color, the more severe the sheath blight disease. These differentiation effects were more apparent compared to the differentiations made by original RGB, multispectral RBG and HLS images. This can be explained that red and near-infrared lights are more sensitive to the changes in canopy color from the healthy green color to the diseased yellow color and the changes in canopy structure from dense to sparse in density caused by sheath blight. Therefore, the vegetation index NDVI is a good indicator of different levels of sheath blight observed in this study.

Image-based NDVIs were also compared to the ground truth NDVIs acquired by GreenSeeker sensor and it was found that there was a strong correlation between them with a high R^2 value of 0.91 and a low RMSE value of 0.0854 (**Figure 11**). Imaged-based NBVIs were selected to determine their ability to quantify the levels of sheath blight. The results demonstrated that there was a good correlation between image-based NDVIs and ground truth sheath blight severity, with a R^2 value of 0.63 and a low RMSE value of 0.0852 (**Figure 12**).

The results of this study show multispectral image has more advantages of color and spectral information than regular RGB image, providing a strong ability to detect the sheath blight disease in the field. Use of multispectral camera can not only detect sheath blight but also quantify different levels of the disease in the field. An UAV equipped with a multispectral camera can be a new tool to aid in scouting and monitoring the development of sheath blight in rice.

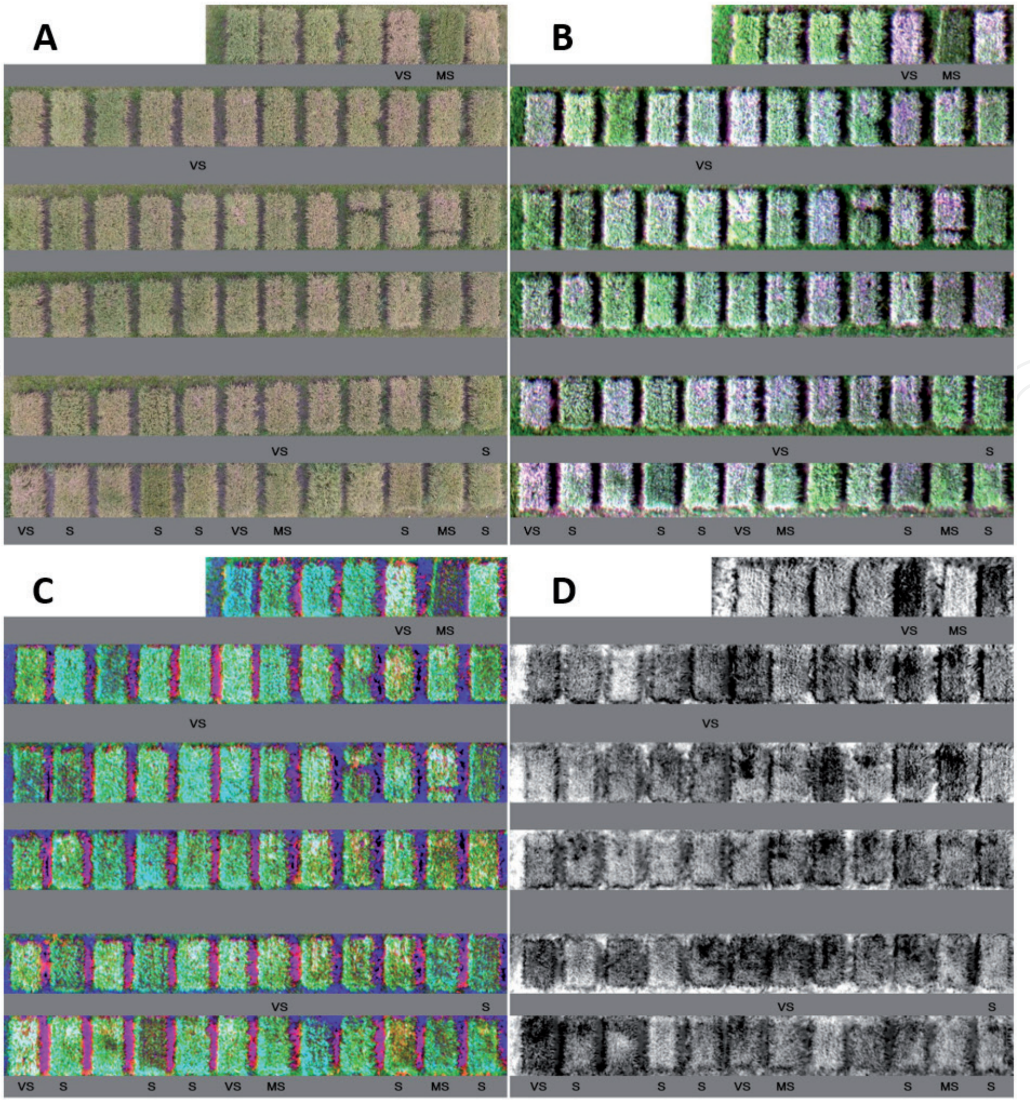

Figure 10.
Original RGB (A), multispectral RGB (B), HLS (C), and NDVI (D) images of 67 field plots, with rice cultivars and elite breeding lines having different levels of resistance to sheath blight, at Beaumont, Texas, USA (source: [38]). VS = very susceptible; S = susceptible, and MS = moderately susceptible.

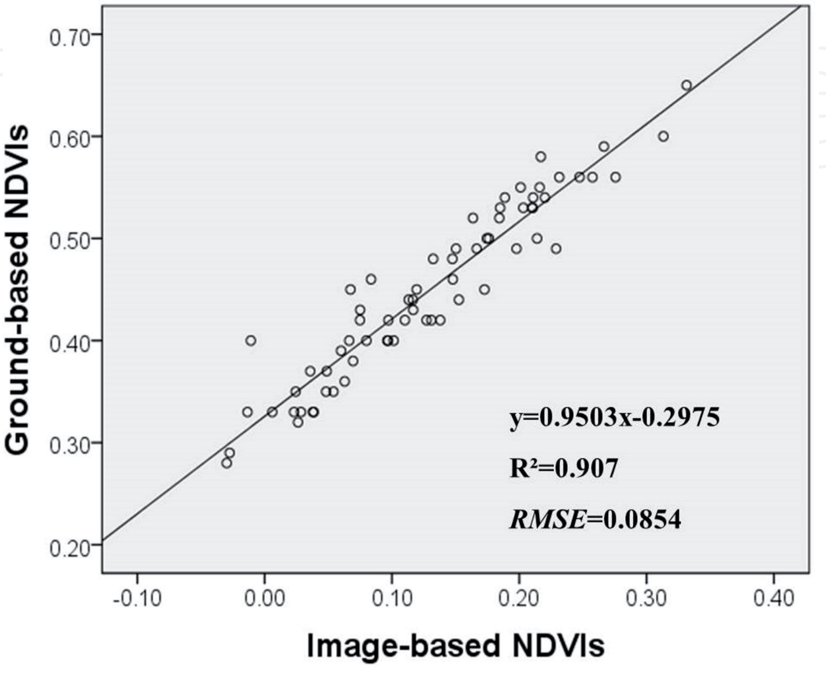

Figure 11.
Correlation between image-based NDVIs and ground-based NDVIs (source: [38]).

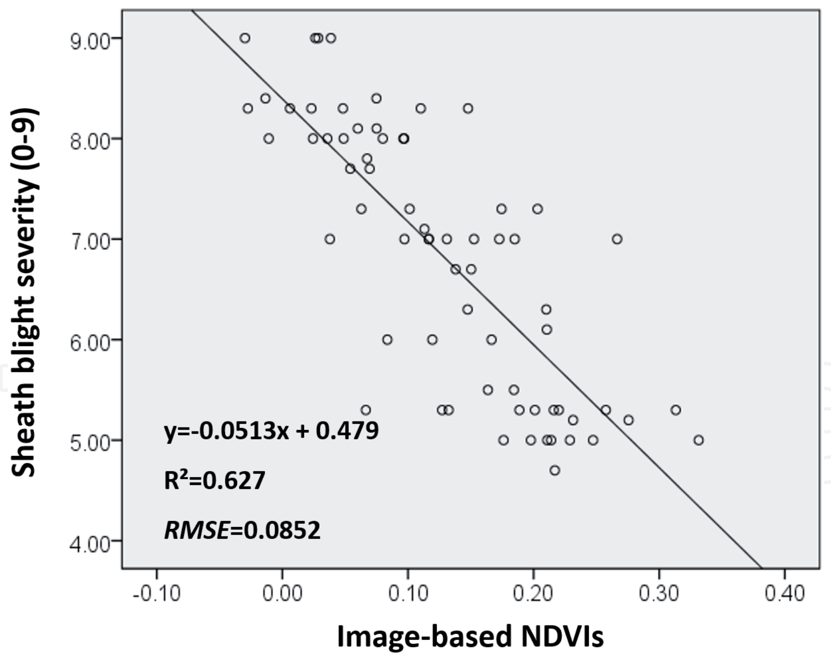

Figure 12.
Correlation between image-based NDVIs and ground truth sheath blight severity (source: [38]).

4.4 UAV remote sensing for NBLS detection

The spread of NBLS in the field is different from the spread of sheath blight. NBLS spreads by air-borne spores and its distribution in the field is uniform whereas sheath blight is soilborne and it spreads in the field in an aggregated pattern. A study was conducted at Texas A&M AgriLife Research Center, Beaumont, TX, USA to evaluate the performance of UAV remote sensing on the detection and quantification of the NBLS disease in field research plots [41]. Rice cultivar Presidio, susceptible to NBLS, was seed drilled in 40 plots (**Figure 13**). Plots consisted of seven 4.9-m rows, spaced 18 cm between rows, with field blocks separated by 2.7-m wide allies. NBLS developed from natural inoculum and the symptoms initially appeared at the tillering stage and developed progressively with time, reaching high levels of disease severity as rice approached maturity. Differentiation in NBLS severity among the 40 plots was achieved by applying with 10 different

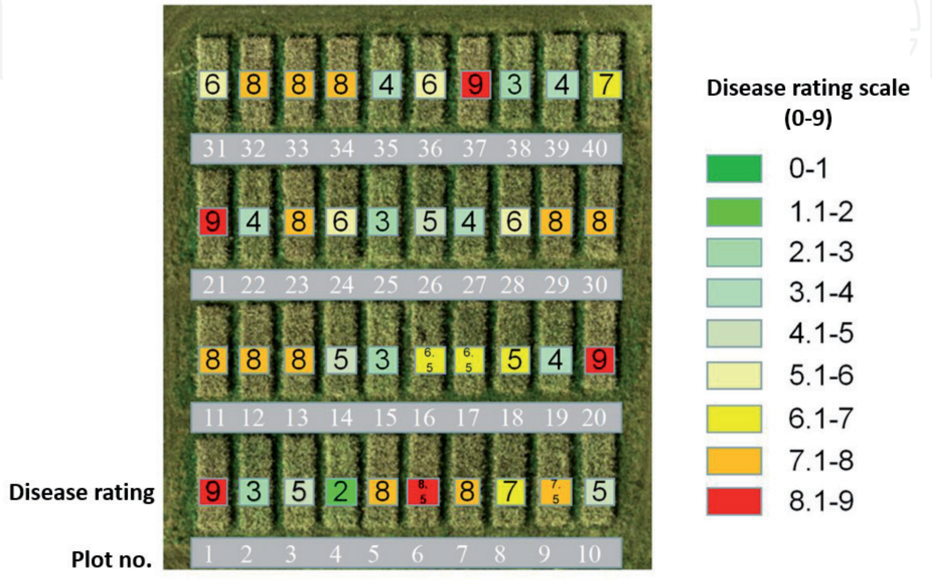

Figure 13.
Field plots and narrow brown leaf spot (NBLS) severity ratings at Beaumont, Texas, USA (source: [41]).

fungicide treatments at the mid-boot stage. NBLS severity was rated by visual symptoms on a scale of 0 to 9 where 0 represents no symptoms and 9 represents most severe in symptoms and damage (leaves dead) (**Figure 13**).

Four-rotor DJI INSPIRE 2 UAV equipped with Sentera Multispectral Double 4 K sensor was used to capture field plot images (**Figure 14**). The multispectral camera offers five spectral bands of blue, green, red, red edge, and near-infrared (NIR) and can capture 12.3 MP still images. UAV images were acquired by flying the UAV over the field plots at the altitudes of 10 and 15 m, with a ground sampling resolution of 0.42 and 0.63 cm, respectively. Image data were preprocessed for image mosaic, radiation correction, and band coincidence using Photoscan 1.4.1 and Envi

Figure 14.
Four-rotor DJI INSPIRE 2 UAV equipped with Sentera Multispectral Double 4K camera used in this study.

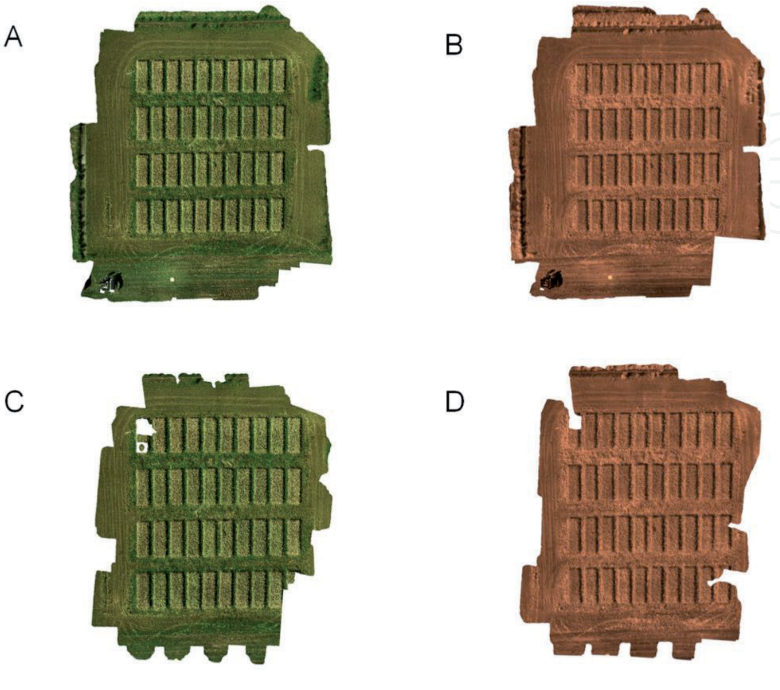

Figure 15.
RGB (A) and NIR (B) images at the 10-m flight altitude, and RGB (C) and NIR (D) images at the 15-m altitude (source: [41]).

5.3 software. Different vegetation indices (Vis) and color space HIS, HSV, HSL and YCbCr were extracted from the ENVI mass cut images and used to determine their performance on the detection of different levels of NBLS severity at the two flight altitudes. Most effective vegetation index and color space were selected and the inversion model of NBLS with good correlation was developed to predict the levels of NBLS severity.

Results of comparison of the correlations between Vis or color features calculated from RGB image and NIR image (**Figure 15**) and NBLS severity indicate that using RGB image was more suitable for the assessment of NBLS than NIR image and that Excess Green minus Excess Red (EXGR) at the 15-m flight altitude was the best vegetation index to detect and quantify the different levels of NBLS severity (R^2 = 0.89, $RMSE$ = 0.70). This vegetation index offers more spectral information than other vegetation indexes and thus it is more effective to detect the NBLS disease. It is also found that the EXGR is more effective to detect high levels of the NBLS disease. The findings from this study demonstrate that it is feasible to use UAV multispectral sensor to detect and assess the levels of NBLS in the field.

5. UAV used as a tool for disease management

Disease detection, decision making, and control action are the three essential steps for effective management of crop diseases. UAV remote sensing itself cannot directly serve for control of plant disease. However, it provides an innovative tool for disease assessment. Effective disease assessment can ensure to make a correct decision that results in employing a proper control measure for control of a crop disease. Fungicide application is one of the most effective control measures for disease management. With the development of UAV technology, the use of UAV for aerial fungicide application has become a new means for control of diseases in rice and other crops in recent years [15].

Since the first UAV used for aerial insecticide applications to control insect pests in rice, soybean and wheat in Japan in 1990 [68], UAV-based aerial spraying technology has developed quickly in agricultural aviation applications, especially in the last five years [15]. UAV aerial application has several advantages over traditional aircraft aerial spraying and ground application. UAV sprayer can operate at low altitude and suspend in the air to achieve high-precision positioning with GPS [15], which can reduce pesticide draft potential and the amount of pesticides used [18]. Its downward airflow generated by rotors can help pesticide droplets penetrate dense canopies to improve application efficacy. UAV sprayer can operate on high crops and in areas with steep or mountainous terrains and can cover a large area whereas ground application is unable to do so. UAV aerial spraying is lower costs and more flexible in operation than typical aircraft aerial application. Because of these advantages, research and use of UAV aerial spraying technology have been increased quickly in recent years in many countries, especially China and Japan. In 2016, there were 4,262 UAV sprayers in operation and more than 476,000 hectares of field crops, including rice, treated with UAV aerial sprays in China [15]. In the 2020 statistics, there were approximately 170 types of pesticide application UAVs, and 55,000 UAVs flown; treated crop areas were more than 450 million hectares in China [16]. In Japan, use of UAV is widespread and more than 2,000 UAV applicators are in operation to spray approximately 40% of the rice acreage [17, 18].

Helicopter and quadcopter are among the most common UAVs applicators used to spray fungicides, insecticides, and herbicides in various field crops [69, 70]. Tank capacity and duration of flight are two key technical parameters of UAVs. Although they vary with UAV, most UAVs have the tank capacity of 16 to 20 litters and the duration of flight of less than 30 minutes at present [16]. Flight altitude usually ranges from 2 to 10 m depended on individual UAVs [69, 70]. Spraying swath width can range from 3 to 15 m, and work efficiency can be anywhere from 0.7 to 13 hectares per hour. Optimization of these operation parameters are important to improve spraying efficacy. Research has been conducted to determine flight altitude, flight speed, and spraying swath width that are more suitable for various UAVs. For example, using WPH642 helicopter to spray on rice, the best flight altitude was found to be 2 m and the best flight speed was 1.5 m per second whereas for P20 quad-rotor UAV, the best flight altitude was 2 m and the best flight speed was 3.7 m per second [69]. Selection of optimal operation parameters can achieve optimum spray droplet deposition into canopies to improve spraying efficacy. Flight speed, flight altitude, and nozzle flow rate are three factors in order of importance that affect droplet deposition distribution [69].

UAV sprayers have the advantages of low equipment costs, low fuel consumption, low spraying volumes, no pesticide contamination risks to operators, and high productivity compared to traditional big aircrafts and ground tractors [18]. With recent advances in UAV development and communication technology, research and use of UAVs for applications of fungicides and other pesticides have been significantly increased in field crops, including rice, in China, Japan, India and many other countries. However, it is expected that UAV aerial spraying cannot replace more conventional means such as aircraft aerial application. Among other disadvantages, UAV sprayers are small in tank capacity and cannot load large amount of pesticides for large farms, especially rice farms in the US with an average of 243 hectares per farm [33]. UAV applications have significantly short duration of flight and cannot cover large spray area a time. On the other hand, UAV sprayers can be used in situations where they can be advantageous. UAV spraying technology can be incorporated into current crop production systems for precision fungicide applications [56]. Precision applications can be more effective to control diseases that develop in cluster patterns like rice sheath blight. In the US, application of UAV remote sensing for crop disease detection and the use of UAV for pesticide application in rice and other field crops are still in its infancy. The US falls behind other countries, especially China, in research and use of UAV remote sensing in plant disease detection and management. Continued research and more monetary investment are needed in research and adopting this new technology to keep up with other countries like China and Japan, which is worthy as much as $10 billion US dollars a year in productivity [17].

6. Conclusion and prospects

Quick and accurate diagnosis and detection of rice diseases, especially sheath blight, are the first essential step for effective disease management to reduce production costs and maximize production returns. However, traditional disease detection methods based on visual symptoms are time-consuming and laborious, and its accuracy is highly dependent on the knowledge and experience of the inspector. UAV remote sensing provides an unprecedented spectral, spatial, and temporal resolution that can distinguish diseased tissue, plant and cropped area from healthy tissue, plant and cropped area based on the characteristics of disease symptoms. Sheath blight and NBLS have their own characteristics in symptoms and disease development pattern. Among the five remote sensors commonly used for assessing abiotic and biotic stresses of crops, RGB sensor, multispectral sensor, and hyperspectral sensor have been successfully used to detect sheath blight; multispectral sensor has been used to detect and quantify NBLS; and infrared thermal sensor can be used to detect the occurrence of rice blast. So far, there have been no reports on the use of fluorescence imaging for rice disease detection. Multi-rotors, helicopters, fixed wings, blimps, and flying wings are among the most UAVs used for crop phenotyping and disease detection. Selection of a suitable unmanned aerial system is important to acquire best imaging data that can be processed and modeled for the detection and quantification of crop diseases. Each UAV has its advantages and disadvantages in costs, flying ability, and payload capacity; each sensor has its own advantages and limitations in acquiring spectral information. In addition, UAV can also be used as an innovative aerial fungicide applicator for disease control. UAV sprayers can operate at low altitudes, fly with various speeds, and apply with low fungicide volumes, making it more suitable for situations where precision fungicide applications are needed for more economically and environmentally effective control of diseases such as rice sheath blight with cluster occurrence. The use of UAV for pesticide application has become a new disease control practice in rice and other crops in many countries, especially China and Japan.

However, applications of UAV technology on disease detection and fungicide application are still in the early stages of development. There remain many technical limitations and application challenges in the research and development of these technologies. Current UAV systems have limited battery capacity, tank capacity and payload. Sensors are usually expensive. There is lack of supporting technologies for UAV-based aerial spraying, such as optimization of nozzle-related canopy deposition, and the formulations of pesticide materials and adjuvants specific for UAV spraying. Although the UAV industry growth is very quickly in recent years, there is apparent lack of standard design of UAVs (rotor designs, types of engines, tank sizes, and nozzles types), which creates challenges for agrichemical manufacturers to develop recommended guidelines for product use. There needs the development and improvement of methods for big image data processing and disease detection model establishment. Early disease detection is critical for timely fungicide application for effective disease control. However, most UAV remote sensing methods reported in the literature are less effective for the detection of diseases at the early stages, such as rice sheath blight and NBLS described in this article. Current strict airspace regulations enforced for UAV operations in most countries, especially the US, limit the research and development of UAV-related technologies. Therefore, the progress on the adoption and commercialization of UAV technologies depends on collaborative research between agronomists and engineers, effective education and extension, partnerships between agricultural UAV manufactures and chemical manufacturers, and effective airspace regulations for UAVs. With improving performance of UAVs on flight duration and payload, reduced costs of sensors, and the development and improvement of methods for big image data processing and models for disease detection and monitoring, it is expected that UAV remote sensing will become an effective tool widely used for the detection of diseases in rice and other crops and that UAV spraying technology can become a new means for control of many crop diseases in situations where traditional aircraft aerial spraying and ground spraying are unavailable or infeasible. Along with research breakthroughs of digitalization and artificial intelligence for precision application across fertilizer, pest, and crop management needs, this innovative UAV technology will become a core tool in a farmer's precision equipment mix in the future.

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