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DISEASE DETECTION IN CITRUS CROPS USING OPTICAL AND THERMAL REMOTE SENSING: A LITERATURE REVIEW

Victória Hellena Matusevicius e de Castro[1]*, Taya Cristo Parreiras[2] & Édson Luis Bolfe[3]

1 - State University of Campinas, Faculty of Agricultural Engineering, Campinas, São Paulo, Brazil

2 - State University of Campinas, Institute of Geosciences, Campinas, São Paulo, Brazil

3 - EMBRAPA Agricultura Digital, State University of Campinas, Institute of Geosciences, Campinas, São Paulo, Brazil

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ABSTRACT

Brazil stands out in the international citrus trade, especially due to its oranges, having produced around 16 million tons in 2021. However, productivity could be increased with greater control of diseases such as greening, which has spread around the world and leads to the total loss of affected trees. Given this scenario, it is necessary to perform fast and accurate detections in order to better manage actions and inputs. Since remote sensing is a pillar of digital agriculture, a literature review was carried out to analyze the use of optical and thermal sensors for the detection of diseases that affect citrus groves. For this purpose, the international databases *Scopus* and *Web of Science* were used to select references published between 2012 and 2022, resulting in twelve studies — most from China or the United States of America. The results showed a prevalence of methodologies that combine bands and spectral indices obtained through the use of multispectral and hyperspectral sensors, predominantly on board unmanned aircrafts (UAVs). Machine learning (ML) and deep learning (DL) classification algorithms produced good results in the detection of citrus groves affected by diseases, mainly greening. These results are affected by the stage of the infection, the presence or absence of symptoms, and the spectral and spatial resolutions of the sensors: the Red-Edge band and data with higher spatial detail result in more accurate classification models. However, the analyzed literature is still inconclusive regarding the early detection of infected plants.

Palavras-chave:
Agricultura digital
Citricultura
NDVI

DETECÇÃO DE DOENÇAS EM CITROS UTILIZANDO SENSORIAMENTO REMOTO ÓPTICO E TÉRMICO: UMA REVISÃO DE LITERATURA

RESUMO

O Brasil se destaca no comércio internacional de citros, principalmente a laranja, e produziu cerca de 16 milhões de toneladas em 2021. Todavia, a produtividade poderia ser aumentada com o maior controle das doenças como o greening, que se espalhou por todo o mundo e leva à perda total das árvores afetadas. Diante desse cenário, é necessário realizar detecções rápidas e precisas para que haja uma melhor gestão de ações e insumos. Tendo em vista que o sensoriamento remoto é cada vez mais aplicado no contexto da agricultura digital, foi realizada uma revisão de literatura referente ao uso de sensores ópticos e termais na detecção de doenças que afetam pomares de citros. Como bases de informações sobre os artigos científicos analisados, utilizou-se os bancos de dados internacionais Scopus e Web of Science, entre 2012 e 2022. Essa análise resultou em doze estudos, com predominância de representação científica na China e Estados Unidos da América. Além de prevalência de metodologias que combinam bandas e índices espectrais, obtidos principalmente por meio de sensores multi e hiperespectrais embarcados em aeronaves não-tripuladas (UAVs). Percebe-se que algoritmos de aprendizado de máquina produzem bons resultados na detecção de pomares de citros afetados por doenças, principalmente o greening. Contudo, os resultados variam de acordo com o estágio da doença, com a ocorrência ou não de sintomas, bem como com a resolução espacial das imagens. A banda Red-Edge e dados de maior detalhamento espacial produzem melhores resultados, porém, a literatura analisada ainda não é conclusiva a respeito da detecção precoce de todas as doenças em citros.

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Email (corresponding author)*: v245192@dac.unicamp.br

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Gabriel Araújo e Silva Ferraz

INTRODUCTION

Estimates indicate that the world population will reach the figure of over 9 billion people by 2050, posing the need to increase food production by 70%, with less environmental degradation, and also with a reduction of deforestation and of agrochemicals (FAO, 2017). In this context, there is a need for Brazil, one of the largest food suppliers on the global market, to restructure production chains aiming at greater efficiency and sustainability, reducing losses and fulfilling the sustainable development objectives defined by the United Nations (UN) (MASSRUHÁ *et al*., 2020).

Brazil is the world's largest producer of oranges and orange juice, and the second-largest producer of citrus (VIDAL, 2022). In 50 years, the country has generated 60 billion dollars in revenue from the export of orange juice in updated values (NEVES *et al*., 2010), and the total national production of the fruit in 2021 was estimated at 16.2 million tons, yielding around R$ 12.5 billion (IBGE, 2023). In addition to having a solid economic impact, citriculture also has significant social relevance, considering that along the citrus production chain, each direct job generates two indirect jobs (NEVES *et al*., 2010). In 2021, there were 44,837 new admissions of workers in the sector (CITRUSBR, 2022).

However, diseases limit the economic benefits and can cause losses of up to 70% in productivity (USDA, 2022): such is the case of citrus greening, also known as Huanglongbing (HLB), with high destructive potential, affecting all commercial varieties (DA GRAÇA, 1991; BOVÉ, 2006); Citrus Variegated Chlorosis (CVC), common in older plants, characterized by symptoms of nutritional deficiency (chlorosis) and reduced fruit size (ROSSETTI & DE NEGRI, 2011); and citrus canker, a severe disease that generates necrotic lesions and is present in about 15% of the stands (GOTO, 1992).

HLB was initially identified and described in the first decades of the 20th century, but it has become the leading cause of losses and increased costs in citrus production in the 21st century, since there is no cure for infected canopies, resulting in a global reduction of about 40% of the productive area in the last 20 years (USDA, 2022).

Field inspections and laboratory analyses conducted to detect diseases such as HLB using the polymerase chain reaction (PCR) method are costly and laborious. Moreover, the spatial variation, the inaccessibility of the field, and environmental factors make traceability a challenging task (LI *et al*., 2015; GARZA *et al*., 2020). Since HLB and other diseases cause leaf changes that result in visual indications such as yellowing and spots, the use of remote sensors with high spatial and spectral resolutions can contribute to a fast, accurate and, ideally, early detection of affected plants (NEUPANE; BAYSAL-GUREL, 2021).

Because optical remote sensing (RS) is based on interactions (absorption, transmission or reflection) between electromagnetic radiation (EMR) emitted by the Sun in the form of electromagnetic waves of different lengths (λ) and objects on the surface, which vary according to their biophysical properties, images obtained by remote sensors can be processed and analyzed to obtain spatialized information on crops, including changes caused by diseases (PONZONI *et al*., 2012).

The interaction between EMR and leaves can be analyzed chiefly through three channels captured by optical sensors: the visible channel (VIS), which involves the primary colors blue (B), green (G) and red (R) at wavelengths (λ) between 400 and 720 nm; the near-infrared channel (NIR), at λ values between 720 and 1100 nm; and the medium infrared channel (MIR), between 1100 and 3200 nm. Reflectance variations occur in these channels due to photosynthetic pigments (in VIS), the internal structure of leaves (in NIR) and the presence of water in the plant (in MIR) (PONZONI *et al*., 2012).

Thermal sensors can capture the EMR emitted by elements on the surface in the λ of the thermal infrared (TIR), between 3000 and 14000 nm, converting this information into temperature data. A key variable in plant physiological processes, temperature can undergo variations caused by structural and metabolic changes induced by diseases, and, therefore, capturing these variations with RS can be essential for production management (MESSINA; MODICA, 2020).

In the 1960s, spectral indices were developed using aerial images and field observations. These indices are dimensionless radiometric measurements generated by equations that combine the spectral bands capable of "highlighting" specific characteristics of targets — such as vegetation — in the images and also providing information, for example, about leaf area, green biomass, chlorophyll, and moisture content, facilitating the modeling and analysis of the state of the plants' health, growth and development (HATFIELD *et al*., 2019; PONZONI *et al*., 2012).

In recent years, the potential of RS disease monitoring has been applied to several crops, such as potatoes (AFZAAL *et al*., 2021), avocados (HARIHARAN *et al*., 2019), and pines (DENG *et al*., 2020). In general, the authors combine multispectral and hyperspectral images — very high spectral resolution, in hundreds of short and contiguous bands —, spectral indices, machine learning (ML), and deep learning (DL) algorithms to detect diseases and contribute to the management and application of inputs at variable rates (NEUPANE; BAYSAL-GUREL, 2021).

ML algorithms, such as Random Forest (RF) and Support Vector Machines (SVM), and DL algorithms, such as Convolutional Neural Networks (CNNs) and Radial Basis Function (RBF), are techniques capable of learning from training data of a given problem to automate the generation of analytical models and solve related regression and classification tasks (JANIESH *et al*., 2021).

We must briefly describe the general script for collecting and processing images with RS: i) the light reflected by the leaves of plants is detected by sensors (VIS, multispectral, hyperspectral, or thermal); ii) images in the different bands captured by the sensor are obtained; iii) after the processes of normalization and extraction through algorithms, the volume of data is reduced; iv) the multibands are then stacked; and v) different automation techniques are employed in the classification process (TERENTEV *et al*., 2022).

In this sense, the present study aims to assess, through a literature review, how RS has been used in the identification of diseases that specifically affect citrus growing in Brazil and in the world, identifying tools, analysis techniques, and perspectives based on the results of the studies analyzed in this article.

MATERIAL AND METHODS

This article is based on the RBS Roadmap methodology structured by Conforto *et al*. (2011), which consists of three phases, subdivided into a few steps: 1) entry, the definition of search terms for scientific articles; 2) processing, the verification of the relevance of said articles; and 3) exit, digging into the papers and synthesizing the findings of the bibliography. The list of phases that make up each of these steps is available in Table 1, while Table 2 details the criteria.

In the processing phase, a search was conducted on the *Web of Science* database, the oldest database of scientific publications, used and cited worldwide, covering about 34,000 journals (BIRKLE *et al*., 2020), and on *Scopus*, the most comprehensive database of abstracts and citations for peer-reviewed literature (AL-KHOURY *et al*., 2022), which returned 38 articles published between 2012 and 2022. Excluding duplicates — those not related to the application of remote sensing in the detection of diseases in citrus crops

Table 1. Conducting a systematic literature review based on the RBS Roadmap

1. **Entry**	2. **Processing**	3. **Output**
1.1 Problem	2.1 Conducting the search	3.1 Warnings
1.2 Goal	2.2 Analysis of results	3.2 Registration and filing
1.3 Primary sources	2.3 Documentation	3.3 Synthesizing results
1.4 Search strings		3.4 Theoretical models
1.5 Inclusion criteria		
1.6 Qualification criteria		
1.7 Method and tools		
1.8 Timeline		

Table 2. RBS Roadmap input information focusing on the detection of diseases in citrus crops using remote sensing

Steps	Details
1.1 Problem	Is remote sensing a reliable non-destructive tool for detecting citrus diseases?
1.2 Goal	Producing a systematic literature review of scientific articles that use RS to detect diseases in citriculture
1.3 Primary sources	Web of Science and Scopus databases
1.4 Search strings	"*Citriculture* AND *disease* AND *remote sensing*", "*Citriculture* AND *disease* AND *UAV*", "*HLB* AND *remote sensing*", "*HLB* AND *UAV*"
1.5 Inclusion criteria	a) Only articles; b) publication between 2012 and 2022
1.6 Qualification criteria	Articles with a descriptive methodology

UAV — Unmanned Aerial Vehicle

— in addition to articles in Mandarin, 12 studies were selected for this analysis.

RESULTS AND DISCUSSION

Amount, period and origin of the analyzed studies

In the period selected for this study, there was a concentration of research in 2020, as shown in Figure 1. Out of the 12 studies analyzed, 8 (66%) were published between 2018 and 2020. Furthermore, 11 studies aim to detect greening (HLB), the most destructive citrus disease worldwide, which has no known cure and no variety is resistant or immune (MORIYA *et al*., 2019; GARZA *et al*., 2020).

Regarding the origin of the studies, there was a large concentration of publications from China (5 articles), linked to the China Agricultural University, and also from the United States (4 studies), developed by the Citrus Research and Education Center at the University of Florida. The global distribution of these publications can be seen in Figure 2.

The concentration of research in China can be explained by the fact that it is the world's largest producer of citrus and one of the most affected countries by HLB. In 2022–2023, the country is expected to produce around 33.5 million tons of oranges and tangerines (USDA, 2022). The USA, the country with the second highest number of papers on the subject, is the fifth largest citrus

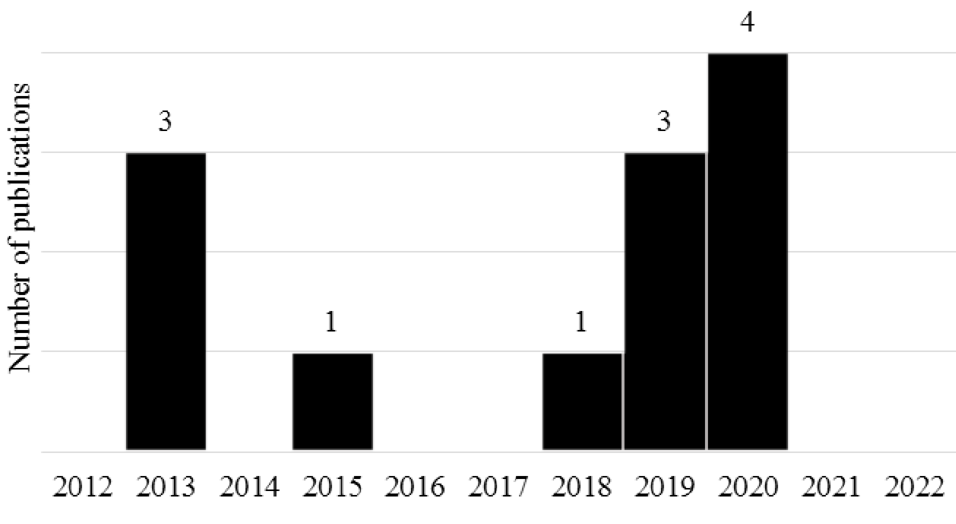

Figure 1. Distribution by publishing year of articles focusing on the detection of diseases in citrus crops using remote sensing

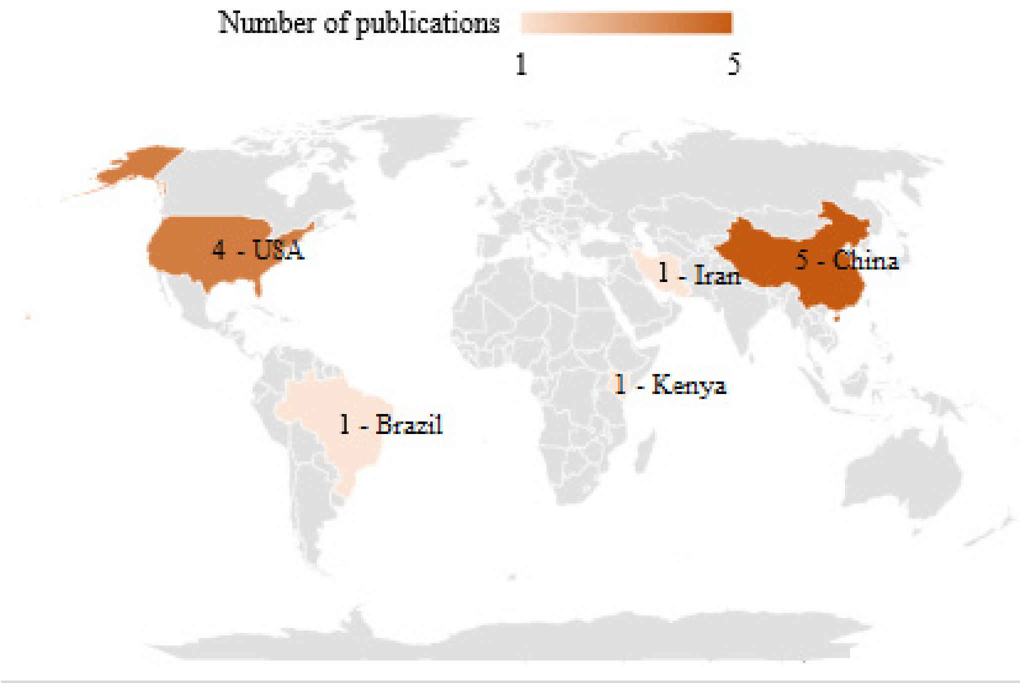

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Figure 2. Worldwide distribution of the analyzed studies focusing on the detection of diseases in citrus crops using remote sensing

producer in the world, and also one of the most affected countries by the disease, suffering a reduction of over 60% in production in the last 20 years as a result of the spreading of the disease and the worsening climate conditions (USDA, 2022).

Platforms, sensors and resolutions

In the selected studies, we found images being captured by orbital, suborbital and terrestrial sensors. At the orbital level, two studies used images from the North American commercial satellite WorldView-2, attached to a multispectral sensor (MS) that operates in 8 bands between 400 and 1040 nm; 1.85 m of spatial resolution and 1.1 days of temporal resolution, in addition to a panchromatic band of 0.46 m.

Another two studies were carried out using multi and hyperspectral sensors on board small manned aircrafts, which flew over the experimental fields at approximately 650 m altitude, resulting in a spatial resolution of 0.5 m. Multirotor unmanned aircrafts, or Unmanned Aerial Vehicles (UAVs), used in 8 studies (66%), were the leading imaging platform chosen to map the occurrence of diseases in citrus groves.

UAVs are flexible and efficient imaging platforms, seeing as they can be equipped with various sensors and fly over the terrain at low altitudes (20–100 m, mainly), resulting in images of very high spatial resolution (in centimeters), in addition to presenting a higher frequency of imaging and being easy to operate (MANFREDA *et al.*, 2018). Finally, a study was conducted exclusively using a terrestrial hyperspectral sensor attached to a utility vehicle.

Regarding spectral resolutions, the sensors operated between the wavelengths of 400 and 1000 nm, in different configurations: multispectral, from 4 to 12 bands; hyperspectral, from 25 to 128 short bands; and visible (only B, G and R), in addition to a test that used a sensor capable of operating in thermal infrared, aiming to capture the temperature variation of plants infected by diseases. Figure 3 shows the distribution of studies by types of sensor, including visible (RGB), thermal, multispectral and hyperspectral. Figure 4, in turn, illustrates some examples of platforms and sensors used in the selected studies.

None of the selected studies used the Light Detection and Ranging (LIDAR) optical and

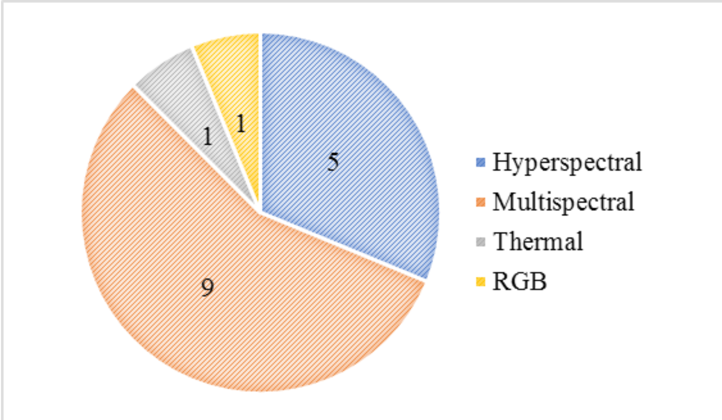

Figure 3. Types of remote sensors used to detect diseases in citrus crops found in this study

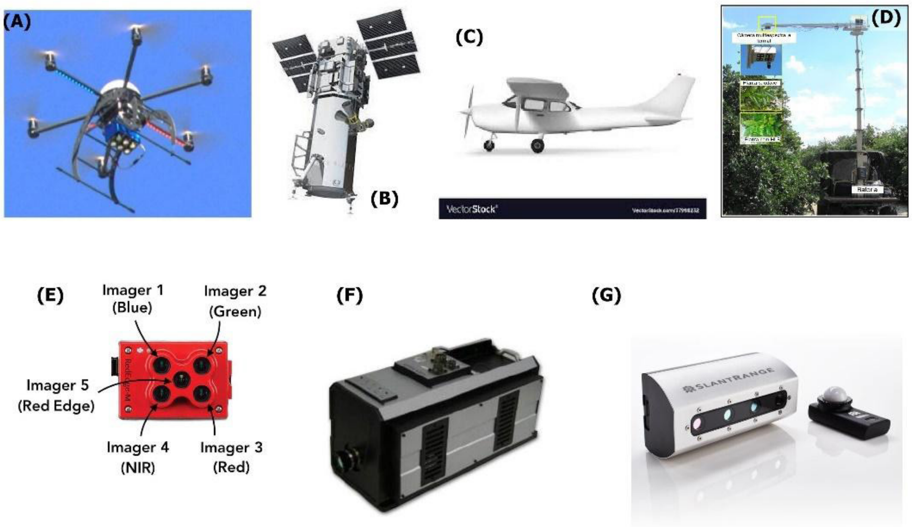

Figure 4. Examples of platforms and remote sensors used to detect diseases in citrus crops in the selected studies. (A) HiSystems multirotor UAV attached to a miniMCA6 multispectral sensor, Tetracam; (B) WorldView-2 satellite (provided for illustrative purposes); (C) single-engine fixed-wing aircraft (provided for illustrative purposes); (D) utility vehicle attached to MCA multispectral and thermal sensors, MIC-005, Tetracam Inc.; (E) MicaSense Red-Edge sensor that can be attached to a UAV; (F) AISA EAGLE VNIR hyperspectral image sensor that was attached to a manned aircraft; (G) SlantRange 3P multispectral sensor that can be attached to a multirotor UAV

active sensor technology. LIDAR sensors, which can operate in near and mid-infrared, emit laser pulses, calculating the distance of an imaged object using the elapsed time between the light traveling until its reflection back to the sensor. This technology has been tested in the detection of diseases because it includes depth as an analysis variable, generating three-dimensional information; on the other hand, it implies a high cost of acquisition and specificities of operation and processing (NEUPANE; BAYSAL-GUREL, 2021).

Analysis methods and main results

After the analysis of the selected studies, it was concluded that the leading methodology for detecting diseases in citrus cultivation involves the application of classification algorithms based on machine learning to generate maps identifying healthy plants and plants affected by the disease in question, as seen in Garcia-Ruiz *et al*. (2013), Li *et al*. (2015), Moriya *et al*. (2019) and others, which will be discussed ahead.

Figure 5 illustrates the most common process for generating disease detection maps in citriculture, based on the selected studies, which were carried out mainly with passive, optical and thermal sensors:

1. Procuring field data and information to validate remote sensing prediction models: this data concerns the geolocation of healthy and infected plants, and is acquired through the use of high-resolution Global Positioning System by Satellite (GPS) devices and laboratory analyses of the leaves, in addition to spectroradiometer data, containing the reflectance of targets acquired with spectroradiometers in the field or laboratory (Figure 5.1);
2. Procuring aerial or orbital images, mainly with UAVs (Figure 5.2): it is worth mentioning that using long time series is not common, and images usually come from one or two dates;
3. The images can be used to extract primary reflectance values in the different bands and, more commonly, are used to generate spectral indices (Figure 5.3);
4. Statistical analysis of band values (optical and thermal) and spectral indices is performed to look for significant differences between healthy and diseased plants, or they can become input data in predictive models generated with different classification algorithms, such as Support Vector Machine (SVM) and Spectral Angle Mapper (SAM), among others (Figure 5.4);
5. Maps indicating the spatial distribution of healthy or infected plants — or detection maps — are generated, which may or may not specify the stage of the disease or the presence of symptoms (Figure 5.5).

Over 50 spectral indices figure in the selected studies being used to check for significant variance between healthy and diseased plants, and also comprising the input database for classification models. It is important to emphasize that hyperspectral sensors allow the creation of variations of an index with different wavelengths of the same band, since they can capture data in narrower bands. Thus, the Normalized Difference Vegetation Index (NDVI), for example, can be drawn with different NIR and R band combinations. Table 3 shows some vegetation indices considered more efficient in their differentiation between healthy citrus plants and those affected by diseases by the selected studies.

Regarding supervised classification, a methodology that utilizes algorithms to recognize predetermined classes — such as the occurrence of a specific disease (e.g., yes or no) —, 16 classifiers (or algorithms) were identified. However, the most commonly used in the detection of diseases in citrus groves were SVM (in four studies) and SAM (in four studies); in addition to Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), Random Forest (RF), neural networks (NN) and MahaDist, all appearing in two studies. The performance of these classifiers varied from case to case.

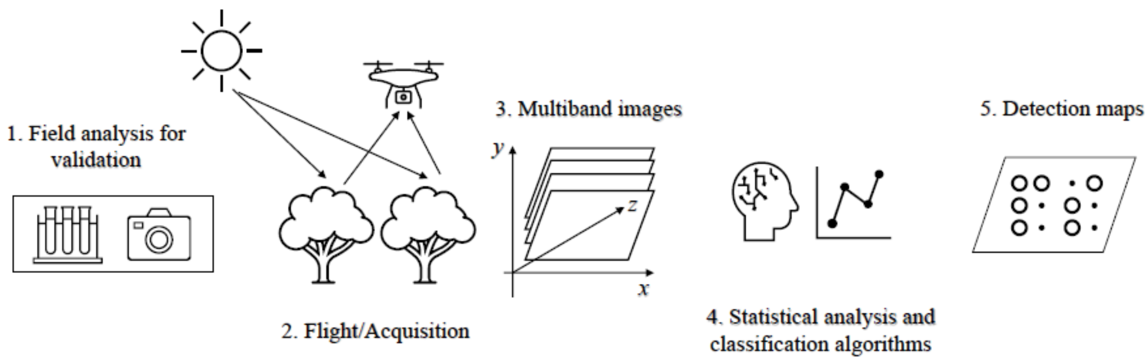

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Figure 5. Example of a common scheme for procuring and analyzing remote sensing data to generate classification models and detection maps of disease occurrence in citrus crops. The process is illustrated with an UAV acquisition platform, but it can be carried out with other platforms (orbital, suborbital and terrestrial)

Table 3. Examples of vegetation indices used to map the occurrence of diseases in citrus groves in the selected studies

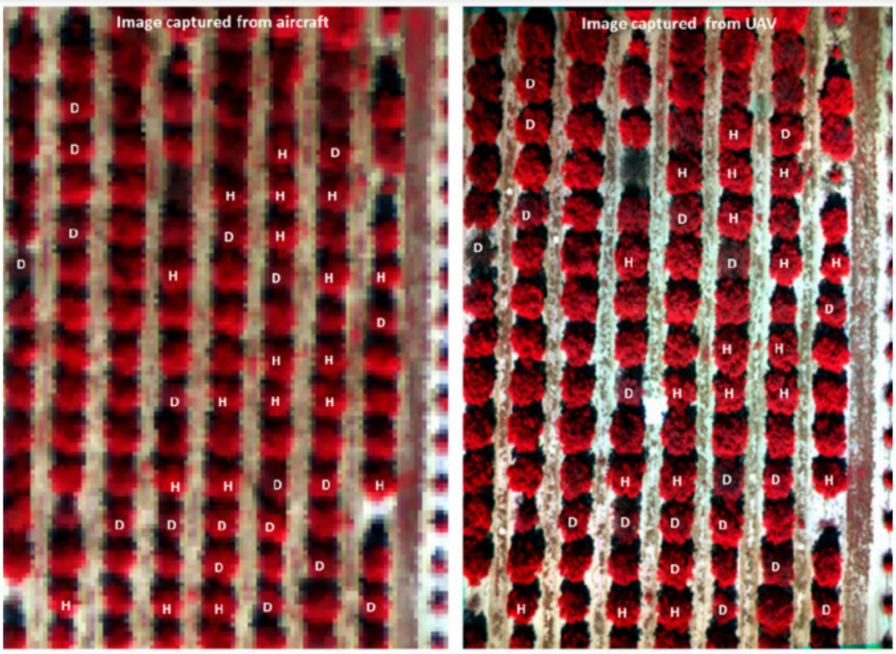
Vegetation Index	Acronym	Equation	References
Anthocyanin Reflectance Index	ARI	R (550 nm) / R (700 nm)	Abdulridha *et al.* (2019)
Chlorophyll Index	CI	(NIR – G) -1	Pourazar *et al.* (2019)
Chlorophyll Vegetation Index	CVI	NIR*(R / G²)	Deng *et al.* (2020); Lan *et al.* (2020)
Green Normalized Difference Vegetation Index	GNDVI	(NIR – G) / (NIR + G)	Abdulridha *et al.* (2019); Pourazar *et al.* (2019)
Green Normalized Difference Vegetation Index	GNDVI_RE	(RE – G) / (RE + G)	Li *et al.* (2015)
Modified Soil Adjusted Vegetation Index	MSAVI	((2 × NIR+1) − √ ((2×NIR + 1)2 − 8 × (NIR − R) 2))) / 2	Chang *et al.* (2020)
Red Edge Normalized Difference Vegetation Index	NDRE	(NIR – RE) / (NIR + RE)	Abdulridha *et al.* (2019)
Normalized Difference Vegetation Index	NDVI	(NIR – R) / (NIR + R)	Deng *et al.* (2020); Lan *et al.* (2020)
Structure Intensive Pigment Index	SIPI	(NIR – B) / (NIR – R)	Pourazar *et al.* (2019); Lan *et al.* (2020)
Simple Ratio Index	SRI	NIR (ou RE) / R	Li *et al.* (2015)
Transform chlorophyll absorption in reflectance index	TCARI	3*[(R740 − R651) – 0,2 (R740 − R581)*(R740/R651)]	Abdulridha *et al.* (2019)

NIR — near infrared; R — red; G — green; B — blue; RE — Red Edge

Garcia-Ruiz *et al*. (2013) compared the detection of infected trees through images obtained by two different aerial platforms: (1) an aircraft equipped with an Aisa Eagle Vnir hyperspectral sensor; and (2) a UAV, capable of flying only at low altitudes with a miniMCA6 multispectral sensor, Tetracam. The images captured by (1) and (2), shown in Figure 6, exhibit previously selected healthy (H) and infected (D) trees, illustrating the disparity generated by the different spatial resolutions. The focus of the study was a plantation in Florida (United States) of 17 hectares of Valencia oranges (*Citrus sinensis valencia*) that used the Swingle rootstock system, which is more resistant to diseases.

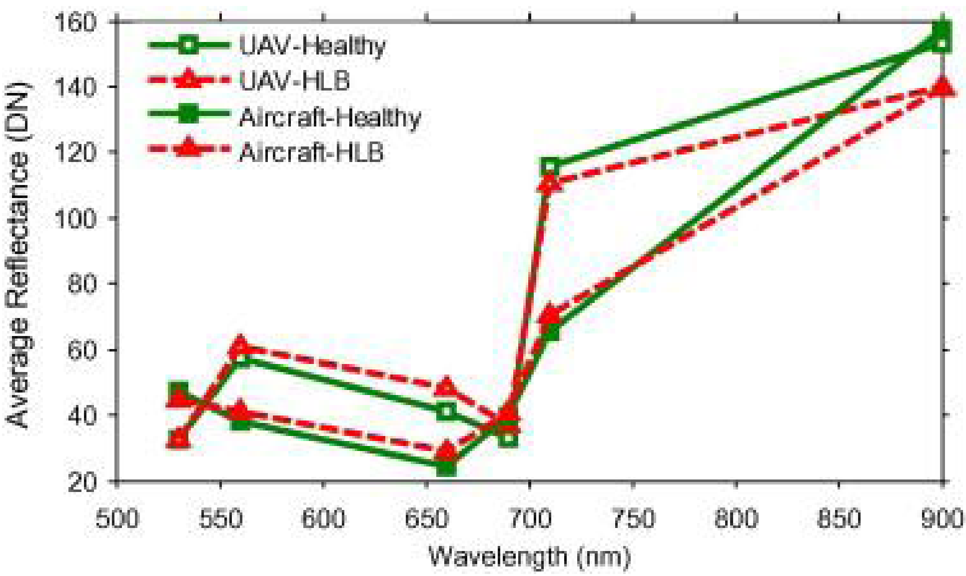
The authors (GARCIA-RUIZ *et al*., 2013) used six spectral bands (530, 560, 660, 690, 710, and 900 nm) common to both sensors, and seven spectral indices (NDVI, GNDVI, SAVI, NIR - red (R), R/NIR, green (G)/R and NIR/R), selected based on previous studies. The classifiers were SVM, LDA and Quadratic Discriminant Analysis (QDA). The highest accuracy in detecting diseased plants was 85%, with a false negative rate of 11%.

The images obtained by UAVs provide up to 100 times more pixels than those obtained from the plane, and this level of detail is due to the lower altitude while capturing images, since the scale of vertical aerial photography is inversely proportional to the height of the flight above ground level (JENSEN, 2009). However, altitude also explains the lower accuracy (74%) and higher figure of false negatives (45%) in images obtained by airplanes. Nevertheless, both plane and UAV images made it possible to detect affected plants. Figure 7 reveals that the average reflectance acquired via UAV and manned aircraft differs between healthy and diseased plants (GARCIA-RUIZ *et al*., 2013).



Source: Garcia-Ruiz *et al*. (2013)

Figure 6. On the left, the image captured by a mini MCA6 multispectral sensor on board a manned aircraft flying at a height of 640 m, with a spatial resolution of 0.5 m/pixel. On the right, the same experimental plot was imaged by a multispectral sensor with a UAV at a height of 100 m, with a spatial resolution of 5.45 cm/pixel



Source: Garcia-Ruiz *et al*. (2013)

Figure 7. In digital numbers (DN), average reflectance of healthy and HLB-affected plants were obtained with multispectral sensors on board a UAV, at 100 m height, and with a manned aircraft at 640 m

Li *et al*. (2013) sought to compare the results of HLB detection in orange trees with an AISA EAGLE VNIR Hyperspectral Imaging Sensor attached to an aircraft flying at 640 m above the ground in Florida with those obtained with multispectral images from the WorldView-2 (WV-2) satellite on the same date. The authors developed a new methodology for the utilization of the SAM classification algorithm, known as *Extended spectral angle mapping* (ESAM). The method involves the following steps: i) apply a smoothing filter to the spectral data (Savitzky-Golay) to remove noise data and outliers; ii) use the SVM algorithm to separate citrus from background pixels; iii) employ the spectral linear vertex component analysis (VCA) method to select better endmembers, that is, cleaner pixels; iv) apply the SAM algorithm to classify healthy and HLB-affected plants; v) and, finally, in order to remove false-positives, filter the results using the maximum inflection point of the Red Edge (RE) band, at 720 nm, as a parameter.

Regarding the results achieved with ESAM, Li *et al*. (2013) observed that the maturity of the plants has a strong influence over the predictive capacity of the models. The accuracy of the models varied between 63% and 71% with plants in an early or intermediate stage of growth; on the other hand, ESAM identified the occurrence of HLB in mature plants with 86% accuracy. In addition to the fact that younger trees may be less susceptible to diseases, the authors believe that the canopy volume, which is larger in more mature plants, contributes to a lower spectral mixing of the pixels. In contrast, background pixels have a more substantial influence on less-developed canopies. Furthermore, the proposed method outperformed other algorithms, such as the original SAM, MahaDist and K-means.

Sankaran *et al*. (2013) used a multispectral sensor (MIC-005) and a thermal sensor (Tau 640) attached to a utility vehicle, suspended 3 m from the canopy, to analyze the spectral response of 74 Valencia orange trees (*Citrus sinensis Valencia*) in a grove in Florida. In order to find spectral variables to differentiate between healthy and HLB-affected plants, the authors tested the following spectral indices: structure insensitive pigment index (SIPI), Vogelmann red-edge index (VOG), modified red-edge normalized difference vegetation index (m-NDVI), modified red-edge simple ratio (m-SR), red-edge normalized difference vegetation index (RE-NDVI) and NDVI. The average reflectance of trees with HLB was significantly higher for infected healthy trees with RE-NDVI and NDVI. The supervised classification was based on reflectance values in the visible (near-infrared) and thermal bands. According to the authors, the classification algorithm that achieved the highest average accuracy and the highest specificity and sensitivity was SVM, which proved to be very advantageous due to its good self-adaptation, the need for a smaller volume of data for training, and a good level of accuracy. The study concluded that it is possible to detect diseases in plants with a low amount of data by utilizing the occurrence of stress as a verification factor — which can affect the canopy temperature — by using thermal cameras (SANKARAN *et al*., 2013).

Li *et al*. (2015) used multispectral satellite images with ~2 m resolution captured by WorldView-2 to study the capability of detecting HLB in two Valencia orange (*Citrus sinensis Valencia*) plantations in Florida. Two libraries were created, based on field observations: the first one based on very high precision GPS location, and the second with prior knowledge of spectral characteristics of plants in the field. The authors also generated 12 spectral indices and evaluated the HLB detection capability of the following classification algorithms: Minimum Distance (MinDist), Mahalanobis Distance (MahaDist), Spectral Angle Mapper (SAM), Spectral Information divergence (SID) and Mixture Tuned Matched Filtering (MTMF).

The second library, comprised of the reflectance figures measured in the field, presented greater accuracy (average of 74%) than the first library (average of 69%), with a Kappa coefficient of 0.333, which only included the geolocation. Despite the difference between the two libraries, the results indicate the promising potential of high-resolution multispectral satellites for HLB detection. Even without field spectral data, the NDVI, NDVI_2, NDVI_RE, SRI_2 and GNDVI_2 indices differed significantly between healthy and diseased plants (LI *et al.*, 2015).

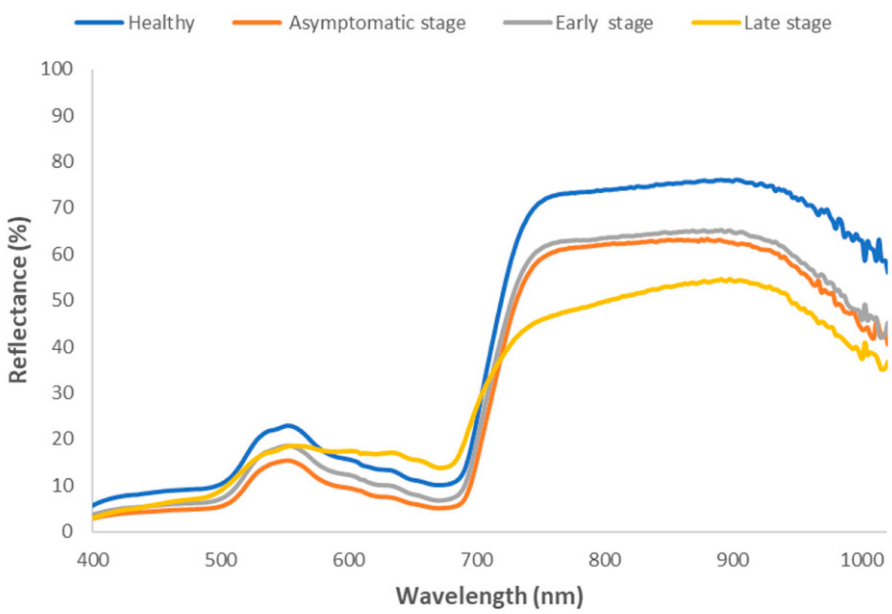
Richard *et al*. (2018) carried out ecological niche modeling, testing the contribution of phenological variables, such as average diurnal temperature interval and precipitation in the wettest/hottest quarter; and vegetation phenological variables derived from spectral indices — e.g., increasing rate at the beginning of the season, falling rate at the end of the season — to predict the distribution of HLB vectors in citrus growing areas in Kenya.

Phenological data was obtained using the Moderate-Resolution Imaging Spectroradiometer (MODIS) multispectral sensor, in resolutions of 250 to 1000 m, on board the Terra and Aqua satellites. Using the MaxEnt algorithm, combinations of land observation data were tested, such as metrics related to phenology, climatic and topographical information, which returned a detection accuracy of 92% and revealed that annual precipitation has an importance of 77% over the prediction of the occurrence of HLB vectors (RICHARD *et al*., 2018).

Abdulridha *et al*. (2019) focused on the identification of citrus canker in Florida Sugar Belle oranges (*Citrus reticulata Clementine* x *Minneola*) using the Radial Basis Function (RBF) and K-Nearest Neighbors (KNN) classification algorithms. The detection carried out *in situ* and in the laboratory led to the determination of the following stages of the disease: i) asymptomatic, leaves without symptoms; ii) initial phase, small lesions; and iii) late phase, brown lesions. First, the Resonon Pika L 2.4 hyperspectral sensor was employed to measure the reflectance of leaves and fruits in the three stages of the disease under laboratory conditions (indoors). The same sensor was then mounted onto a UAV equipped with V-NIR lenses and GPS, which flew over the study area — an experimental field at the University of Florida, 30 m above the ground (outdoors). Using indoor and outdoor images, 31 spectral indices were generated, and then utilized in the RBF and KNN classifications (ABDULRIDHA *et al*., 2019).

For detection under laboratory conditions, the Water Index (WI) was the most accurate, while the Anthocyanin Reflectance Index (ARI) and Transform Chlorophyll Absorption in Reflectance Index (TCARI) were the most efficient among the UAV indicators. The significant difference in the reflectance value of near-infrared bands, mainly between 800 and 900 nm, between leaves at different stages contributes to better detection performance (Figure 8). With UAV data, it was possible to detect the occurrence of canker in citrus crops with up to 100% accuracy (RBF method) (ABDULRIDHA *et al*., 2019).

Moriya *et al.* (2019) verified the existence of diseased plants in a field of 4,777 Christmas orange trees (*Citrus Sinensis*) with Rangpur Lemon (*Citrus bigarade*) grafting in Santa Cruz do Rio Pardo - SP (Brazil). A hyperspectral Rikola model DT-0014 camera was on board a UAV at an altitude of 800 m, and the images it captured were processed to minimize the Bidirectional Reflectance Distribution Function (BRDF). The authors generated detection maps of plants



Source: Abdulridha *et al*. (2019)

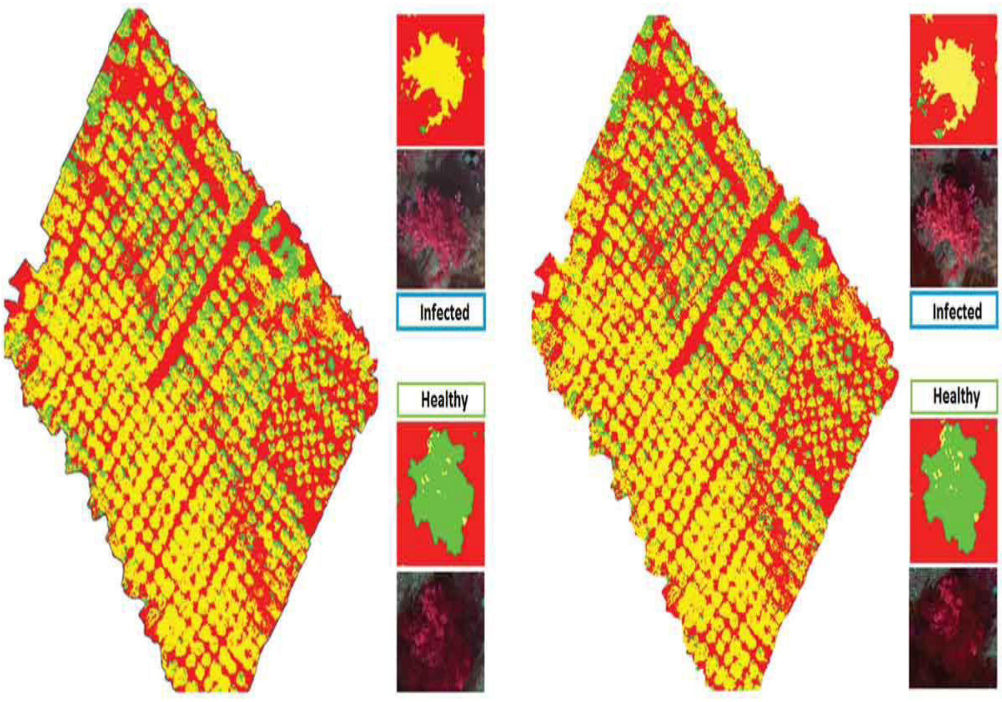
Figure 8. Different reflectance rates at different wavelengths in various stages of canker infection in citrus cultivation

with HLB symptoms using the SAM algorithm, reaching an accuracy of 61.2%. The authors raised the hypothesis that the accuracy could be greater if there were no trees of other species bordering the grove, which may have induced classification errors. It is essential to highlight that the overflight was carried out at 800 m. In general, other authors performed flights at altitudes of up to 100 m, resulting in higher spatial resolution, which may reduce the observed spectral mixing and minimize classification confusion (MORIYA *et al*., 2019).

Pourazar *et al*. (2019) evaluated the potential of multispectral images captured with the MicaSense RedEdge sensor attached to a multirotor UAV to distinguish HLB-infected plants from healthy ones in two different study areas. After a selection stage, the authors observed that the R, NIR and RE bands showed a more significant difference between healthy and sick objects. The model generated with an RF algorithm, which included these bands and other derived spectral indices, achieved an accuracy of 85% detecting diseased plants. Figure 9 shows the final detection map of HLB-affected plants. Furthermore, they showed that the radiometric calibration step, performed with a calibration target from the sensor itself, did not improve the results. However, the authors emphasized that calibration is only necessary for data obtained on the same date, under the same atmospheric and lighting conditions.

Chang *et al*. (2020) also used the MicaSense RedEdge multispectral camera, on board a UAV, to analyze variations in morphological characteristics and the spectral indices of infected and healthy canopies of Hamlin oranges in Florida. The authors showed that canopy volume, effectively estimated with UAV images, is a variable related to HLB infestation. Furthermore, spectral indices of healthy and infected trees presented statistical differences — mainly the NDVI and indices based on RE.

Deng *et al*. (2020) analyzed the stage of HLB symptoms with a Cubert S185 hyperspectral camera attached to the DJI Matrice 600 Pro UAV, at 60 m from Ponca tangerine groves (*Citrus reticulata Blanco*) in Guangdong Province, China. All of the studies mentioned so far obtained information about the health of the trees via PCR tests. Moreover, the authors also resampled the bands from data collected from a terrestrial Hyperspectral sensor — the ASD FieldSpec — to analyze the correlation of the two data sources, and carried



Source: Adapted from Pourazar *et al*. (2019)

Figure 9. Final detection map of HLB occurrence in citrus groves, generated with spectral indices of UAV images and Random Forest algorithm

out a classification with the neural network sparse autoencoder (SAE) to detect infected plants. The degree of correlation between data obtained with a UAV and FieldSpec was 0.96 for both healthy and infected canopies. The neural network based on multiple layers, using 62 vegetative indices and 15 spectral parameters, showed an accuracy of 99.72% in the detection of infected plants, both in the test and validation subsets. The classifier consistently managed to represent the extent of HLB in canopies, differentiating those with more or less than 50% of their canopies affected, thus indicating the stage of the infection (DENG *et al*., 2020).

Garza *et al*. (2020) evaluated the correlation between remote sensing data and biophysical-chemical variations of HLB and gummosis in grapefruit (*Citrus paradisi Macf*) using Swingle-type rootstocks through a camera equipped with an RGB system (true-color) attached to a UAV. The results indicate that variations in the triangular vegetation index (TGI) are partially explained by differences in chlorophyll content, leaf area index and nutritional status (Na, Fe, Ca and K) of plants affected by HLB or gummosis, concluding that the TGI value was higher in unaffected plants. Despite not applying any algorithm for the classification or geolocalized detection of affected plants, the authors revealed that a low-cost UAV sensor system using only the R, G, and B bands can generate variables to supply classification algorithms.

Lan *et al*. (2020), with a multispectral camera (ADClite) attached to a DJI M100 UAV flying 60 m over a grove with 334 orange trees in China, obtained images in G, R and NIR, and performed correlation analysis in derived spectral indices. This data was used to feed several Machine Learning algorithms, and also to detect trees with HLB. The authors observed that, despite the wide variety of indices, the high correlation between them can be counterproductive, so the application of linear and non-linear methods of dimensionality reduction, such as principal component analysis (PCA) and AutoEnconder, can be fundamental to improve the efficiency of the models. Among the analyzed classifiers, AdaBoost and neural networks (NN) presented the most robust performance, with a detection rate of 97%.

The selected studies indicate that ML and DL algorithms can efficiently detect diseases in citrus trees with multi and hyperspectral images. Deep learning models, in general, perform better when confronted with machine learning algorithms, such as RF and SVM, for example, a finding that applies for the monitoring of other crops (NEUPANE; BAYSAL-GUREL, 2021). However, DL neural networks are more demanding in terms of training data volume, and their performance is sensitive to hyperparameter adjustment (NEUPANE; BAYSAL-GUREL, 2021).

In comparison, the very high-resolution images obtained from UAVs contributed to generating more accurate classification models about the data captured by small manned aircrafts and, especially, satellite images. Thus, the studies analyzed here reaffirmed the importance of UAVs for precision agriculture.

Furthermore, it is essential to highlight that during the analysis, RE bands — pure or in spectral indices — were the most important variables to the production of more accurate models to detect diseases in citrus groves. The Red Edge is a region of the electromagnetic spectrum, centered approximately at 700–770 nm, in the transition between chlorophyll absorption at red wavelengths and leaf/canopy scattering at NIR wavelengths, with a degree of reflectance that is more sensitive to different levels of stress from various causes (EITEL *et al*., 2011; IMRAN *et al*., 2020). The RE bands, increasingly applied in the agricultural context, are promising for the early detection of diseases, being available in orbital sensors such as the Multispectral Instrument (MSI) from Sentinel-2, and in many mounted sensors for precision agriculture.

Finally, it is vital to note that the studies were conducted with citrus and rootstock varieties. Valencia oranges are more resistant to HLB on the Carrizo rootstock (SANTOS, 2013), although there are no conclusive results under other conditions. Storey & Walker (1998) state that the grafting system affects root permeability and, therefore, the level of spreading, which can impact detection by remote sensing. Further studies could track variations that may result from the type of crop and rootstock. Chart 1 summarizes variables, methods and main results from the selected studies.

Chart 1. Diseases, platforms, spectral resolution, methods and main results seen in the selected studies, with the objective of detecting via remote sensing plants and citrus canopies affected by diseases

Reference	Disease(s)	Platform(s)	Spectral resolution	Methods/Classifiers	Main results
Garcia-Ruiz *et al.* (2013)	HLB	Single-engine aircraft and multirotor UAV	530–900 nm (Multispectral)	Classification: Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA)	NIR-R index and 710 nm reflectance show larger difference margins between healthy and diseased plants. Classifications with SVM achieve higher accuracy and lower false negative rates. Using a UAV, the false negative rates drop by up to 30%.
Li *et al.* (2013)	HLB	Aircraft; satellite (WorldView-2)	400–1000 nm (Hyperspectral and Multispectral)	Classification: Extended spectral angle mapping (ESAM), K-means and MahaDist	ESAM is a method capable of outperforming other classification algorithms, reaching an accuracy of up to 86% in detecting the occurrence of HLB in citrus groves. The selection of pure pixels and the filtering of false positives with the maximum inflection point of the Red Edge band were fundamental steps for the results. The canopy development stage interferes with the models' performance.
Sankaran *et al.* (2013)	HLB	Ground sensors	440–900 nm, including thermal (Multispectral)	Classification: LDA, QDA, Bagged Decision Tree (BDT) and SVM	Bands at 560 nm and 710 nm show good separability rates for affected plants. Variation in plant temperature caused by stress can be captured with the thermal band. SVM led to models with higher detection accuracy and lower false negative rates.
Li *et al.* (2015)	HLB	Satellite (WorldView-2)	450–800 nm (Multispectral)	Rating: Minimum Distance (MinDist), Mahalanobis Distance (MahaDist), Spectral Angle Mapper (SAM), Spectral Information divergence (SID), Mixture Tuned Matched Filtering (MTMF)	All IVs tested showed statistically significant differences between healthy and diseased plants when supplemented with field spectrometry. Without this information, only NDVI1, NDVI2, NDVI_RE, SRI2 and GNDVI2 differ significantly. Among the classifiers, MahaDist achieved the best performance, with an accuracy of 81%. The classification with satellite images with a 0.5 m resolution benefits from the spectral data obtained with a terrestrial sensor.
Abdulridha *et al.* (2019)	Canker	Multirotor UAV	400–1000 nm (Hyperspectral)	Classification: Radial Basis Function (RBF) and k-Nearest Neighbor (KNN)	Canker detection presented accuracy rates higher than 90% with RBF and KNN, mainly the former. The ARI and TCARI indices present better performance for detection with a UAV. Detection is more accurate with mature and symptomatic plants.

Moriya *et al.* (2019)	HLB	UAV	500–900 nm (Hyperspectral)	Rating: Spectral Angle Mapper (SAM)	The final map showed an accuracy of 61% in detecting plants with HLB symptoms.
Pourazar *et al.* (2019)	HLB	Multirotor UAV	B, G, R, RE, NIR (Multispectral)	Classification: Random Forest (RF)	Use of spectral bands and 12 spectral indices led the RF to detect infected plants with producer and user accuracy above 92%.
Chang *et al.* (2020)	HLB	UAV	560–830 nm (Multispectral)	Correlation analysis and linear regression; Student's T test	Structural traits such as height, canopy diameter and canopy volume, factors to differentiate between healthy and diseased plants, can be estimated with an accuracy of up to 88% with high-resolution UAV multispectral images. The canopy volume of healthy plants is up to 2 times greater because HLB impairs vegetative growth. The NDVI, NDRE, MSAVI and especially CI indices vary significantly between positive and negative plants tested for HLB.
Deng *et al.* (2020)	HLB	Multirotor UAV	450–950 nm (Hyperspectral)	Classification: SVM, stacked autoencoder (SAE) neural networks	Hyperspectral data collected on the ground and via UAV showed a correlation of 0.96. SVM is used for canopy extraction. The wavelengths of 468, 504, 512, 516, 528, 536, 632, 680 and 688 contribute to a better detection capacity of the models. SAE models with 62 IVs and 15 canopy spectral parameters (e.g., peak, trough, location) yielded 99% accuracy in the detection of HLB.
Garza *et al.* (2020)	HLB and gummosis	UAV	580–670 nm (Visible)	Correlation analysis, Student's t test and stepwise regression	Non-infected plants presented higher values of TGI, vegetation index generated only using the visible bands. TGI can explain the presence of gummose 61% of Na, Fe, Ca and K content variations. Although further analysis is required, the study showed that plants with HLB and gummosis can be monitored using low-cost UAV images.
Lan *et al.* (2020)	HLB	Multirotor UAV	G, R, NIR (Multispectral)	Classification: SVM, KNN, logistic regression (LR), RF, Neural Networks (NN) and AdaBoost	AdaBoost models and Neural Networks supplied with spectral indices are appropriate for the detection of affected plants, with accuracy rates of 97%. The variable selection step with linear and non-linear methods, such as PCA and AutoEnconder, is fundamental to reducing redundancies and dimensionality. Different stages of the disease lead to variability in the models.

CONCLUSIONS

- The scientific articles selected from the international databases *Scopus* and *Web of Science* indicate the efficiency and feasibility of optical and thermal sensors for the detection and monitoring of citrus diseases, especially those mounted in UAVs, due to the extremely high spatial resolution. The results from these studies revealed that Red Edge (RE) and near-infrared (NIR) bands and derived indices are more efficient in the detection of diseases, since their reflectance varies between healthy and infected canopies. Algorithms based on machine learning (ML) and deep learning (DL) present good performance rates and can be used to detect citrus diseases. For more complex problems, such as detection at different stages of infections, deep learning is a more appropriate choice.
- However, there are challenges for the general use of this tool: the variations resulting from a smaller amount of spectral bands, the high cost of acquiring equipment for operation and processing, as well as the acquisition of sensors, especially hyperspectral. Although it is possible to state, based on the analyzed literature, that images with higher spatial resolution — such as those obtained by unmanned aircrafts (UAVs) — present better results, the ability to detect diseases in the early stages, especially without symptoms, is still not conclusive.
- Finally, the presence of only one study carried out in Brazil in the international databases *Scopus* and *Web of Science*, based on the search criteria adopted, suggests the need to expand the literature review to other databases, such as *Portal de Periódicos Capes*, and to carry out new studies of this nature in the country.

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CASTRO, V.H.M.: Conceptualization, Formal Analysis, Investigation, Methodology, Writing – original draft; **PARREIRAS, T.C.:** Formal Analysis, Investigation, Visualization, Writing – original draft; **BOLFE, E.L.:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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