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Review

Remote Sensing Technologies Using UAVs for Pest and Disease Monitoring: A Review Centered on Date Palm Trees

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Abstract: This review is aimed at exploring the use of remote sensing technology with a focus on Unmanned Aerial Vehicles (UAVs) in monitoring and management of palm pests and diseases with a special focus on date palms. It highlights the most common sensor types, ranging from passive sensors such as RGB, multispectral, hyperspectral, and thermal as well as active sensors such as light detection and ranging (LiDAR), expounding on their unique functions and gains as far as the detection of pest infestation and disease symptoms is concerned. Indices derived from UAV multispectral and hyperspectral sensors are used to assess their usefulness in vegetation health monitoring and plant physiological changes. Other UAVs are equipped with thermal sensors to identify water stress and temperature anomalies associated with the presence of pests and diseases. Furthermore, the review discusses how LiDAR technology can be used to capture detailed 3D canopy structures as well as volume changes that may occur during the progressing stages of a date palm infection. Besides, the paper examines how machine learning algorithms have been incorporated into remote sensing technologies to ensure high accuracy levels in detecting diseases or pests. This paper aims to present a comprehensive outline for future research focusing on modern methodologies, technological improvements, and direction for the efficient application of UAV-based remote sensing in managing palm tree pests and diseases.

Keywords: UAV; palm tree; pests; red palm weevil; multispectral; thermal; LiDAR

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1. Introduction

For many years, traditional techniques used in monitoring and detecting pests in date palms have primarily relied on manual surveys, visual inspections, and labor-intensive fieldwork requiring expert knowledge. Though they have formed the basis of pest management measures for ages, these methods are associated with several drawbacks such as being subjective by nature, time-consuming, and inefficient at identifying infestations in their early stages. In addition, timely recognition and intervention become more difficult due to the widespread occurrence of pest attacks such as by the red palm weevil (RPW) over extensive geographical areas. This often results in irreversible damage to date palm ecosystems and to means of livelihood [1–3].

As a result of pest infestations, date palm agriculture, which has always been the cornerstone of the cultural and economic heritage of arid regions across the world, is under threat. Date palms now grow on more than 1 million hectares around the world, with a production of about 9.5 million metric tons per year, whilst the oil palm industry globally contributes to an economy of USD 60 billion and has a cultivation area of about 18 million hectares [4–6]. Major pests, such as the red palm weevil (RPW) and Bayoud disease, have caused billions in losses in the recent past. Hence, there is an urgent need for advanced monitoring and management systems that apply modern technologies, such as remote sensing, to mitigate the spread and impact of these threats.

The RPW responsible for this destruction in date palm plantations causes irreparable damage to trees, leading to significant economic loss for farmers and agricultural economies. Farmers experience a direct economic impact due to reduced yields and the costs of pest control interventions. This is accompanied by supply chain disruptions and financial losses for various stakeholders in the agricultural industry, such as the market, suppliers, etc. Better pest detection tools have a double advantage; they prevent early infestation and reduce labor as well as other resources used in traditional methods of controlling pests, hence making it possible for farmers to adopt more sustainable agricultural practices.

Consequently, agricultural scientists and practitioners are continuously seeking novel and efficient strategies to combat RPW infestation and protect date palm agriculture [7–9]. Recently, there has been a range of approaches and devices for identifying the RPW, which today includes innovative technologies such as audio detection systems to capture the noise made by the bugs while they feed on the date palm trees and X-ray systems to take internal images of tree structures showing infestation [10–12]. However, these methods have their limitations. Audio detection systems can be affected by environmental noise and may not detect early-stage infestations, while X-ray systems are costly, require significant setup, and are limited to individual trees [13].

Recent advancements in remote sensing technologies, particularly the emergence of unmanned aerial vehicles (UAVs)—commonly referred to as drones—equipped with thermal sensors, offer unprecedented opportunities to revolutionize pest management strategies in date palm agriculture [8,9]. UAVs rapidly gained traction as versatile platforms for aerial data acquisition, enabling researchers and practitioners to capture high-resolution imagery of agricultural landscapes with unparalleled precision and efficiency [1,2,14]. Unlike RGB imaging, multispectral, hyperspectral, and thermal imaging involves capturing images across multiple wavelengths of light, providing valuable additional information about plant health, stress levels, and physiological conditions. These imaging techniques offer enhanced spectral resolution, allowing for the detection of subtle variations in vegetation properties that are not visible in standard RGB imagery. The key benefits of using remote sensing technology for monitoring plant diseases and pests can be summarized as follows [15–19]:

- Plants diseases and pests can be monitored using remote sensing techniques that do not require physical interaction with the plants. This enables non-contact surveillance over large areas, providing vital data on the spatial distribution of diseases and pests.
- Remote sensing tools can retrieve many types of data, including—for instance—spectral, thermal, and radar information, which consequently indicate disease- and pest-caused changes in plant health states. This process efficiently acquires timely data concerning plant status.
- Combine remote sensing methods with plant pathology theories, allowing researchers to develop a better understanding of agricultural systems. This helps differentiate between different diseases and pests, assess infection severity levels, and create maps at various levels.
- Remote sensing has been useful in practical applications, such as precision spraying for disease and pest control, high throughput phenotyping within plants, and loss assessment in agricultural insurance investigations.
- Remote sensing technology can improve the accuracy of disease and pest monitoring by utilizing advanced algorithms and machine learning techniques. These methods go beyond conventional spectral features and statistical approaches, allowing for more precise detection and monitoring of plant health issues.

- Remote sensing enables quick and effective data acquisition across wide areas, hence large-scale coverage. This is in contrast to ground-based field techniques, which are time-consuming and cost-intensive when applied over large regions.
- Remote sensing offers temporal analysis. Tracking these temporal changes is very important for understanding how diseases evolve and how pests invade ecosystems.

This review paper represents a range of wider research into the use of remote sensing technology, and machine learning techniques for crop monitoring and management, but given the context, it is finally applied to date palm trees. By understanding the findings of several studies, this manuscript shows how such advanced technologies may be applied and modified for pest and disease detection in date palm trees toward improving management practices in date palm agriculture.

2. Remote Sensing for Pest and Disease Monitoring

Researchers can acquire a variety of data on plant health indicators such as spectral reflectance, fluorescence, thermal properties, and structural changes by exploiting diverse remote sensing technologies.

- Visible, red-edge, and near-infrared sensors: These sensors collect data that can help detect variations in plant health caused by diseases or pests through the analysis of vegetation spectral reflectance values. The collected data are frequently used for plant diseases and pest monitoring since the sensors detect minute physiological changes in plants.
- Thermal sensors: These sensors capture surface temperature data, which can reveal important insights into the thermal properties of plants. Temperature variations may indicate stress caused by factors such as diseases, pests, or water deficiency. Thermal data can reveal how plants respond physiologically when attacked by pathogens, allowing for early diagnosis of the disease diagnosis.
- Synthetic aperture radar (SAR) and light detection and ranging (LiDAR) sensors: SAR sensors provide detailed information regarding physical structure, while LiDAR sensors give specific details about canopy geometry as influenced by insect activity. This information helps track any developments related to plant health and identify disease vectors.

In the following sections, we will discuss the possible applications of the aforementioned sensors related to crop monitoring for palm trees and date palm trees specifically. Furthermore, we will explore the potential capabilities of various vegetation indices (VIs).

2.1. Multispectral and Hyperspectral Sensors

In precision agriculture, the importance of multispectral sensors mounted on UAVs is significant for pest and disease detection in crops. These sensors capture information at different wavelengths of the spectrum, which facilitates vegetation health analysis and stress level determination. By using this technology, farmers can detect initial signs of pest infestation or disease outbreaks, allowing for prompt and effective responses. Various studies have indicated that multispectral imaging benefits precision agriculture operations such as crop management and yield prediction [20–23].

Vegetation indices derived from multispectral and hyperspectral sensors are important for assessing plant health and identifying stressors like pests and diseases. Indices such as the Normalized Difference Vegetation Index (NDVI) and/or the Photochemical Reflectance Index (PRI) provide information about photosynthetic pigments—such as chlorophyll content—and photosynthetic activity in plants. These indicators help locate zones with poor conditions and signs of stress before they are visible to the human eyes, enabling early intervention and management. It is worth mentioning that these indices derived from high-resolution UAV imagery can significantly improve the precision of pest and disease monitoring in agricultural fields. Common vegetation indices derived from multispectral and hyperspectral images can be listed in Table 1 as follows [24–26]:

Table 1. Common vegetation indices derived from multispectral and hyperspectral images.

Vegetation Index	Description	References
Normalized Difference Vegetation Index (NDVI)	Reflects the difference between NIR and red-light reflectance; useful for overall vegetation health.	[27,28]
Enhanced Vegetation Index (EVI)	Similar to NDVI but improves sensitivity in high biomass regions and reduces atmospheric influences.	[29,30]
Normalized Difference Red Edge Index (NDRE)	Uses red-edge and NIR bands to provide better sensitivity to chlorophyll content and stress detection.	[31]
Soil Adjusted Vegetation Index (SAVI)	Adjusts for soil brightness influences; useful in areas with sparse vegetation.	[32]
Green Normalized Difference Vegetation Index (GNDVI)	Uses green and NIR bands to enhance sensitivity to chlorophyll content.	[33,34]
Chlorophyll Absorption Ratio Index (CARI)	Sensitive to chlorophyll concentration, useful for detecting changes in pigment levels.	[35]
Transformed Chlorophyll Absorption in Reflectance Index (TCARI)	A modified version of CARI to reduce soil background influence.	[36,37]
Structure Insensitive Pigment Index (SIPI)	Measures the ratio of NIR to blue reflectance; useful for assessing pigment changes while minimizing structural effects.	[38]
Photochemical Reflectance Index (PRI)	Indicates changes in xanthophyll cycle pigments, related to photosynthetic efficiency.	[39,40]
Red Edge Inflection Point (REIP)	Measures the wavelength position of the red edge, susceptible to chlorophyll content and stress levels.	[41,42]

According to the literature, possible applications for palm tree monitoring using multispectral and hyperspectral sensors can be summarized as follows:

- Early disease detection: UAV multispectral and hyperspectral cameras are useful for capturing images for the early detection of diseases and pests in date palm plantations. The anomalies indicating stress or infection in diseased vegetation can be efficiently detected allowing for quick remedial actions [43–46].
- Stress detection and management: Multispectral imagery helps identify environmental stressors like water scarcity, nutrient deficiencies, and high salinity. UAV-based monitoring captures changes in vegetation indices linked to stress response, enabling controlled irrigation, fertilizers application, and soil management practices to ensure optimal health of date palms [47–50]
- Precision agriculture practices: Multispectral UAV-based images support advanced agricultural techniques by providing detailed spatial information about plant health on date palm farms. This information can guide site-specific management practices such as irrigation scheduling, fertilizer applications, frond removal, pest control strategies, optimizing resource utilization, and improving performance [20,51,52].

Therefore, UAV remote sensing data offers new possibilities for monitoring and managing the health status of date palm trees, revealing details about plant growth, stress levels, and diseases and infections. Hyperspectral sensors with narrowband indices, particularly red-edge NDVI, and other specific narrowband VIs, have proven to be the best indicators due to their sensitivity to subtle physiological changes. Figure 1 shows frequently utilized UAV systems equipped with multispectral and hyperspectral sensors. The DJI P4 Multispectral (Figure 1a) and Mavic 3 (Figure 1b) drones both have built-in cameras that collect RGB and multispectral information used for remote sensing in agriculture. However, the Wingtra GEN II (Figure 1c) is suitable for various tasks, including mapping and surveying with the help of multiple cameras including multispectral and RGB. The Matrice 300 RTK (Figure 1d) is designed to use various types of payloads, including Zenmuse P1 and Zenmuse X7, and RedEdge multi-spectral sensors by MicaSense. SPECIM AFX SERIES (Figure 1e) and HySpex Mjolnir (Figure 1f) are equipped with hyperspectral imaging sensors capable of capturing a wide range of wavelengths for detailed analysis of the vegetation.

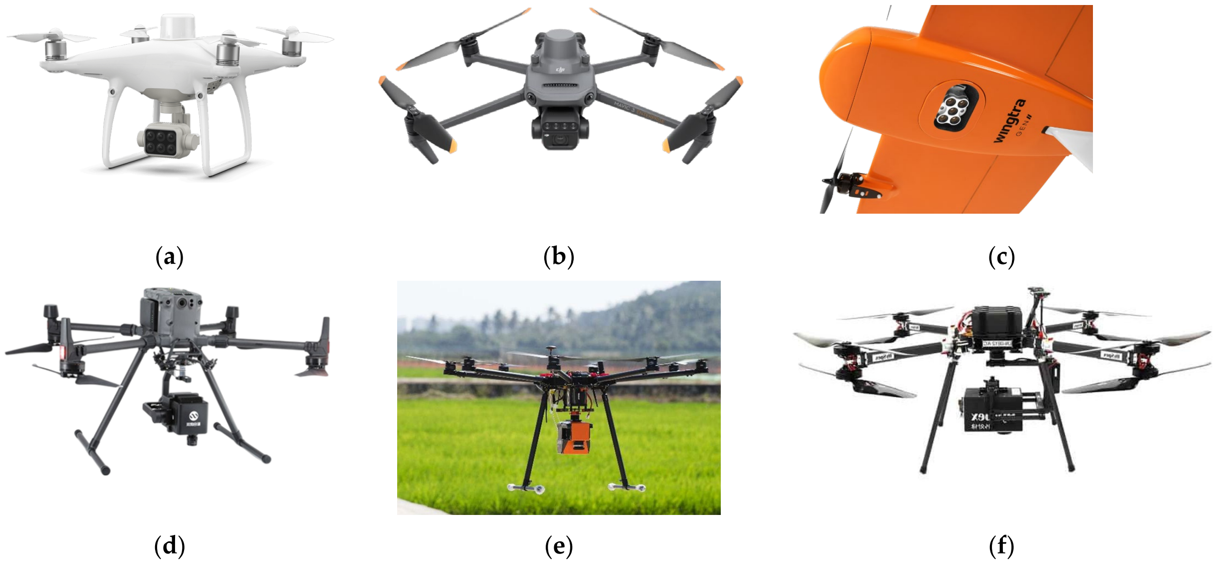

Figure 1. UAV systems with multispectral and hyperspectral sensors. (**a**) DJI P4 Multispectral, (**b**) DJI Mavic 3 Multispectral, (**c**) Wingtra GEN II, (**d**) Matrice 300 RTK, (**e**) SPECIM AFX SERIES, (**f**) HySpex Mjolnir.

Figure 2 summarizes the workflow of using vegetation indices derived from multispectral and hyperspectral sensor images for precision agriculture.

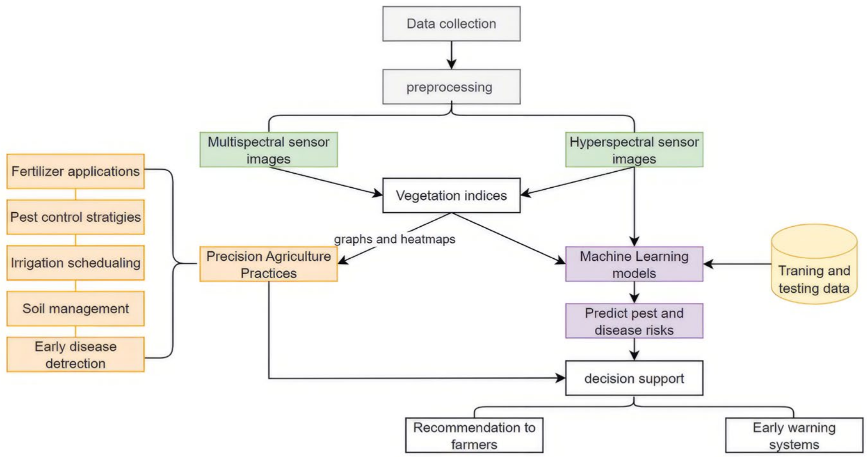

Figure 2. General workflow using vegetation indices derived from multi and hyperspectral sensors for precision agriculture.

2.2. Thermal Sensors

UAVs equipped with thermal sensors play a crucial role in monitoring the health conditions of date palm trees and detecting outbreaks caused by pests like the RPW. These sensors record leaf surface temperatures, which can indicate changes in transpiration rates or heat generated by pest-related fermentation processes in plant tissues due to pest activity. This capability provides valuable information for early detection and management of pest infestations.

For the resilience and sustainability of future date palm agriculture, integrating UAV-based pest management protocols utilizing thermal data is promising. Date palm farms can be remotely surveyed to identify high-risk areas for pest intervention without disrupting normal agricultural operations or requiring extensive fieldwork. This optimization of resource allocation enhances operational efficiency [3,13,53–56].

Current research endeavors have demonstrated the effectiveness of thermal data analysis by UAVs in transforming pest management practices in date palm production. Land surface temperatures (LST) and indices derived from thermal images, such as the Crop Water Stress Index (CWSI) and Thermal Infrared Vegetation Index (TIR VI), have shown good performance in detecting/monitoring RPW as well as in enabling timely interventions to reduce losses incurred through pest attacks in date palm trees. Furthermore, the integration of deep learning using Convolutional Neural Networks (CNNs) and Transformers, has significantly improved accuracy in individual tree detection and mapping, advancing precision agriculture in date palm plantations [54,55]. The important vegetation parameters derived from thermal sensors are:

- Land surface temperature (LST): Measures surface temperature of vegetation—useful for detecting thermal anomalies indicating stress.
- Crop Water Stress Index (CWSI): Evaluates plant water stress levels by comparing canopy temperature to air temperature.
- Thermal Infrared Vegetation Index (TIR VI): Combines thermal data with vegetation indices to enhance stress detection.

Thermal imaging is particularly effective in detecting water stress in crops because it directly measures leaf temperature, which correlates with transpiration activity and leaf conductance. This technique gives reliable and accurate estimates for crop water stress related to leaf conductance as demonstrated by Möller, et al. [57] throughout the entire growing season. By monitoring changes in leaf moisture content, thermal imaging can effectively gauge the Crop Water Stress Index (CWSI) at different stages of plant development, making it possible to continuously monitor the plants' water needs [47]. Additionally, thermal RGB imagery, when combined with computer vision techniques, outperforms traditional RGB imagery in identifying drought-stressed crops with higher classification accuracy rates [58]. Such a comprehensive approach allows for accurate and timely detection of water stress, enabling efficient crop management and irrigation practices.

Accordingly, thermal sensors are highly significant in detecting water stress, hence providing a major contribution to date palm tree pest and disease detection through the following primary ways:

- Physiological response: Plants that lack water demonstrate some physiological changes impacting transpiration behavior leading to changed leaf surface temperatures that can be detected by thermal sensors. Often, such indicators of early stress appear before any visible symptoms of a disease or infestation related to a pest [9].
- Pathogen susceptibility: Water stress can weaken plants, making them more susceptible to pests and pathogens. Hence, the ability to identify stress at an early stage is important for timely management and intervention [59,60].
- Changes in date palm tree trunk temperature: Palm pests like the RPW spend a significant portion of their life cycle within the palm tree trunk, consuming plant tissue. The damage inflicted on the palm tree tissue, along with the debris generated by the pest, initiates a fermentation process that produces heat. This temperature change can be sensed by thermal sensors, thus allowing for the prediction of infected palm trees and upcoming outbreaks [54,56,61].
- Thermal Imaging Sensitivity: Variations in temperatures within the palm tree canopy are detected using thermal imaging, as they may indicate specific stress levels. These variations can signal potential hotspots for pests and diseases even before they spread [9,54]. Worth mentioning that combining thermal data with machine learning models (ML) is an efficient approach to predicting the occurrence of pests and diseases based on detected patterns of water stress. These models can analyze extensive datasets to identify correlations and predict risk. Figure 3 illustrates a summarized workflow of pest and disease detection based on the water stress analysis from thermal remote sensing data [58,60,62,63].

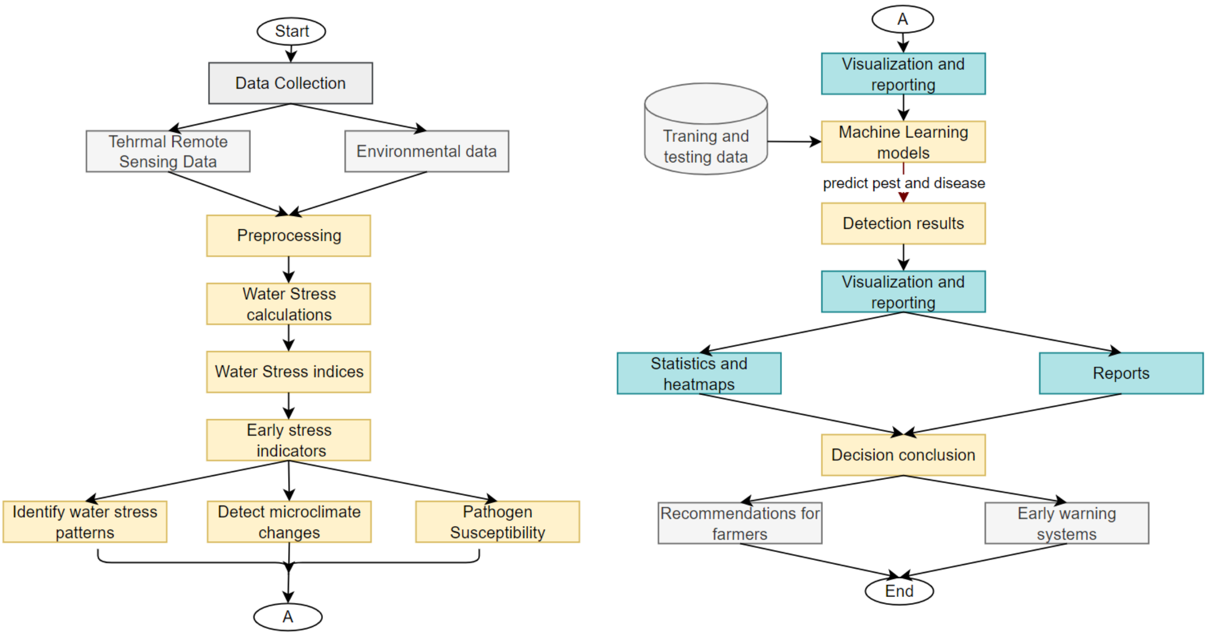

Figure 3. General workflow using water stress analysis for pest and disease detection and relying on thermal remote sensing data.

2.3. Light Detection and Ranging (LiDAR) Sensors

During the past few years, there has been an emergence of using LiDAR technology (ground-based or terrestrial and mobile mapping LiDAR) to aid in conducting all-inclusive forest analysis. LiDAR point clouds provide detailed vertical canopy structure evaluation, tree-by-tree modeling, and species classification. Advanced algorithms and methodologies have been developed using LiDAR data for various applications, from vertical canopy structure analysis to precise individual tree segmentation and species classification. It is important to clarify that valuable vegetation indexes can be derived from the LiDAR data; however, these are not traditional spectral vegetation indices (such as NDVI). Instead, LiDAR-derived indices include:

- Canopy Height Model (CHM): Represents the height of the canopy—useful for assessing growth and detecting structural changes due to pests.
- Leaf Area Index (LAI): Measures the total leaf area per unit ground area, useful for estimating biomass and canopy density.
- Other structural VIs: Include metrics such as canopy cover, tree crown delineation, and volumetric measurements.

Furthermore, LiDAR is excellent for extracting the digital terrain model (DTM) under the canopy, making it well-suited for precise canopy height calculation. This leads to an important question: Is LiDAR technology effective in plant disease detection? To address this, numerous research publications have been reviewed. Recent studies have explored the potential of LiDAR data in detecting plant diseases, including those affecting palm trees. Key characteristics of LiDAR for forestry applications and plant disease detection include the following [64–73].

- LiDAR technology efficiently captures the three-dimensional (3D) structure of vegetation, providing geometric details necessary for disease diagnosis. For example, tree parameters like height, volume, and canopy structure can be measured with high accuracy using a UAV equipped with a LiDAR sensor [64,65,74,75]. Furthermore, the digital terrain model (DTM) that lies beneath the forest is well derived by LiDAR. In this case, a precise estimate of canopy height can only be possible when the DTM below the canopy is adequately established. This makes it especially useful for in-depth vegetation analysis and precision disease detection.

- LiDAR data improve both the detection and understanding of plant stress responses when combined with other imaging techniques, such as multispectral and/or hyperspectral imagery. This integration enables comprehensive analysis of structural and physiological changes related to infections by studying the 3D structures of the trees along with multi-spectral/hyperspectral imagery [64,76,77].
- LiDAR point cloud processing algorithms have high success rates in individual tree segmentation (clustering) which is critical for diseased tree analysis. Segmentation techniques (region growing or parameter domain segmentation) are commonly used for isolating individual trees with their structural attributes analyzed as part of LiDAR-based disease detection methodologies.
    - Region growing segmentation: This technique initiates with the selection of some seed points and then expands outwards to add neighboring points sequentially inwards with regard to a given estimation criterion (e.g., distance, color, surface normal, etc.). It is good in its simplicity and effectiveness for homogeneous regions but performs poorly in handling crown structures and non-uniformity in point distribution [78,79].
    - Parameter domain segmentation: In this approach, the trees are divided into specific groups defined by the used parameters—for example, crown width limited by tree height. This approach especially highlights where dense forest is making it difficult to identify specific trees. On the other hand, however, it has manual parameters to set, which sometimes can be a limitation in using this method in different places [80,81].
    - Model-based segmentation: The specific feature of this method is the attaching of geometric parameters, such as ellipsoid or cylinder, to cloud point data in an attempt to segment the tree structures. It demands heavy computation but comes with the benefit of higher accuracy in tree structures with rather eccentric shapes and canopies. The major disadvantage is the necessity of prior understanding of the tree structure, which limits the approach in forests of great variability [78,82].

These segmentation methods do work and perform their functions appropriate to the environment and the nature of the data acquired from the LiDAR.

- Ground-based LiDAR systems have been particularly effective in detecting specific diseases such as basal stem rot (BSR) in oil palm trees using canopy parameters that were established as good indicators of disease severity [83–88].
- Temporal changes in LiDAR point clouds may be exploited to detect changes in trees, enabling the tracking of disease progression over time. The ability to detect even the smallest structural changes in palm trees allows for the early detection of diseases and timely application of intervention measures [85,89–91].

2.4. Summary of UAV Sensor Applications and Vegetation Indices

The efficacy of UAV sensors in conjunction with vegetation indices (VIs) has been extensively documented in various literature. This review highlights principal studies that have utilized different types of UAV-mounted sensors to derive VIs, enhancing precision in agricultural practices. Multispectral sensors are frequently used to calculate indices such as NDVI and NDR. These indices are essential for assessing plant vigor and chlorophyll content. Hyperspectral sensors capture data across a wide range of narrow bands, enabling the calculation of detailed indices such as PRI and REP for photosynthetic efficiency and plant stress levels, respectively. This is because they cover a very wide variety of colors in their wavelength band, making it easier to see abnormalities in plants before they develop into diseases or irreparable damage. Thermal sensors measure emitted infrared radiation, enabling the computation of indices like CWSI to identify water stress or temperature anomalies indicative of pest infestations and diseases. Additionally, these sensors measure the infrared radiation emitted by objects around them to determine their temperature. This capability provides a means of detecting insects that can cause crop failures during dry seasons, as their temperature is typically higher compared to the surrounding plants (Figure 4).

(**a**) (**b**)

Figure 4. (**a**) True-color image (RGB) of an infected tree, (**b**) a thermal image of an infected palm tree [54].

Furthermore, LiDAR maps depict the canopy structure, highlighting areas where pest and disease damage manifests through biomass loss and poorly formed trees due to defoliation among other indicators.

To conclude Section 2, Table 2 has been created to illustrate the research papers that have focused on using specific sensors mounted on UAVs for tree and crop management and detection. The citations for the listed papers can be found in the references section at the end of this review article.

Table 2. Applications of crop monitoring using different UAV sensors.

Sensor Type	Application Area	Relevant References
Multispectral Cameras	Disease Detection in Trees	[46,92]
	Pest Infestation Mapping	[44,93]
	Early Disease Detection	[94,95]
	Precision Agriculture Applications	[20,51]
	Tree Crown Extraction and Analysis	[96]
Hyperspectral Cameras	Disease and Stress Detection	[44,94]
	Chlorophyll and Water Stress Detection	[48,97]
	Plant Phenotyping and Productivity	[52,70]
	Precision Agriculture and Pest Surveillance	[26,93]
	Detection Methodologies	[17,48]
Thermal Cameras	Disease Detection in Trees and Crops	[54,98]
	Water Stress Detection	[48,99]
	Pest Infestation Monitoring	[100,101]
	Plant Phenotyping	[99,102,103]
	Feasibility and Application Studies	[47,55]
LiDAR	Forest Trees Structure Monitoring	[67,72,88]
	Individual Tree Detection and Segmentation	[68,88]
	Tree-Level Morphometric Traits	[69]
	Species and Provenance Variation Detection	[70]
	Pest and Disease Stress Detection	[73]
	Comparison Studies	[104,105]

The relationship between advanced UAV sensors and vegetation indices, demonstrating their role in enhancing efficiency in palm farming management, is highlighted in Table 3. This survey presents a variety of sensors and indices utilized for palm tree diseases and pest management. For detailed citations of studies considered, refer to the reference section of this paper.

Table 3. Selected literature shows the relationships between each type of UAV sensor and specific vegetation indices for palm tree pest and disease management.

Sensor Type	Index/Feature	Relevant References
Multispectral Cameras	NDVI (Normalized Difference Vegetation Index)	[1,9]
	NDRE (Normalized Difference Red Edge)	[3,50]
	EVI (Enhanced Vegetation Index)	[15,49]
	SAVI (Soil-Adjusted Vegetation Index)	[8]
Hyperspectral Cameras	PRI (Photochemical Reflectance Index)	[49,97]
	NDVI (Normalized Difference Vegetation Index)	[16,17]
	Chlorophyll Fluorescence	[49,97]
Thermal Cameras	LST (Land Surface Temperature)	[54,55,106]
	CWSI (Crop Water Stress Index)	[54,56]
	TIR VI (Thermal Infrared Vegetation Index)	[55]
LiDAR Sensors	3D Canopy Structure	[64,65,77]
	Canopy Volume	[52,66,85]
	CHM (Canopy Height Model)	[74]
	LAI (Leaf Area Index)	[74]

As mentioned, recent advances in UAV technology have substantially improved the monitoring of palm tree pests and diseases. However, some limitations constitute yet a set of challenges for UAV technology to succeed under widespread and effective use in this context, here are some of the challenges:

1. Cost of data acquisition: The initial investment in UAV equipment, along with the cost of regular deployment of UAV flights, may be very expensive for many agricultural practitioners, particularly in developing countries. Such financial barriers to flying UAVs limit the accessibility and scalability of UAV technologies for consistent monitoring. According to [14], UAV technology's cost needs to be lowered if it is to be more widely adopted for agricultural purposes.
2. Processing complexity: UAV data, especially from multispectral, hyperspectral, and LiDAR sensors, involve advanced expertise and software in data analysis and interpretation. Such complexity may hinder or delay decision-making processes and the incorporation of any insight gained from such data sources into pest management strategies [1].
3. Weather impacts: UAV operations are ideally conducted on sunny, cloud-free days with low wind speeds. Weather conditions of strong wind, rain, or extreme temperature, may destabilize the aircraft during flight, leading to poor information and spatial resolution with data, which disables the UAV from being employed during the reference monitoring days [9].

After the discussions of the capabilities and advantages of various UAV sensor technologies in Section 2, more specific applications for monitoring palm tree health will be presented in the following Section 3. A particular focus will be shown on how the sensors have been employed to detect and manage diseases and pests in date palm trees.

3. Palm Tree Pests and Diseases

UAV-based remote-sensing technologies have been used with great success in detecting pests and diseases affecting palm trees. This section provides a brief review of the use of multispectral, hyperspectral, and thermal sensors for the detection of pests and diseases, with emphasis on real-world case studies.

Date and oil palm trees are important agricultural crops that face numerous challenges from pests and disease. These issues typically impact various parts of the tree, including the fronds, leading to observable damage or signs of distress.

Palm tree diseases involve several major and minor economic diseases, besides nutrient deficiencies and this requires having different control strategies depending on the regional and the country's contexts. Table 4 illustrates some of these diseases, pests, and deficiencies.

Table 4. Some of the common diseases, pests, and nutrient deficiencies of palm trees.

Disease/Pest/Nutrient Deficiency	Type	Control Strategy	Reference
Fusarium wilt	Major disease	Fungicides, sanitation	[107]
Ganoderma boninense	Fungal pathogen	Tree removal, fungicides	[108–110]
Basal stem rot (BSR)	Major disease	Soil drenching, fungicides	[110,111]
Red palm weevil (RPW)	Major pest	Pesticides, pheromone traps	[11,112]
Oligonychus Afrasiaticus (Old World date mite)	Minor pest	Miticides, biological control	[113,114]
Dubas bug	Minor pest	Pesticides, biological control	[115,116]
Leaf blight	Minor disease	Pruning infected leaves, fungicides	[117,118]
Leaf spot	Minor disease	Fungicides, good cultural practices	[119]
Phosphorus deficiency	Nutrient deficiency	Phosphorus fertilizers	[120,121]
Potassium deficiency	Nutrient deficiency	Potassium fertilizers	[122]

Many arthropod pests, such as mites and insects, attack date palm trees, and some species target foliage. The damage caused by such pests as the Old World date mite, frond borer, and RPW includes changes in the shape or condition of infested palm tree leaves. Studies [123–125] indicate that in date palm trees, umbrella-shaped fronds can be symptomatic of infestations. Notably, umbrella-like fronds in date palm trees serve as a good indicator of plant stress or a pest problem. This is because some pests, like the frond borer and longhorn date palm stem borer, can cause damage leading to frond breakage or gradual drying. Additionally, the RPW is a significant pest that burrows into the trunk and fronds, causing severe structural damage. Figure 5 illustrates a profile section of a point cloud that was taken on a date palm tree farm in Jordan showing an infected palm tree among healthy palm trees with visibly dead upper fronds.

The palm tree pests are usually managed through chemical pesticides, which may, however, spark secondary pest outbreaks and resistance problems. Therefore, other methods like biological control and the use of light traps for monitoring and mass trapping are also employed [3,123,124,126]. A summary of papers to review that apply research on using remote sensing techniques for the detection of pests and diseases on palm trees is shown in Table 5.

Data obtained from UAV-based remote sensing technologies help determine physical changes within palm trees. Nevertheless, advancements in data processing can further increase the reliability and efficiency of disease and pest detection. The next section will review some of the machine learning and deep learning techniques that are used to analyze sensor data for more precise and automated detection of diseases and pests in crops and palm trees.

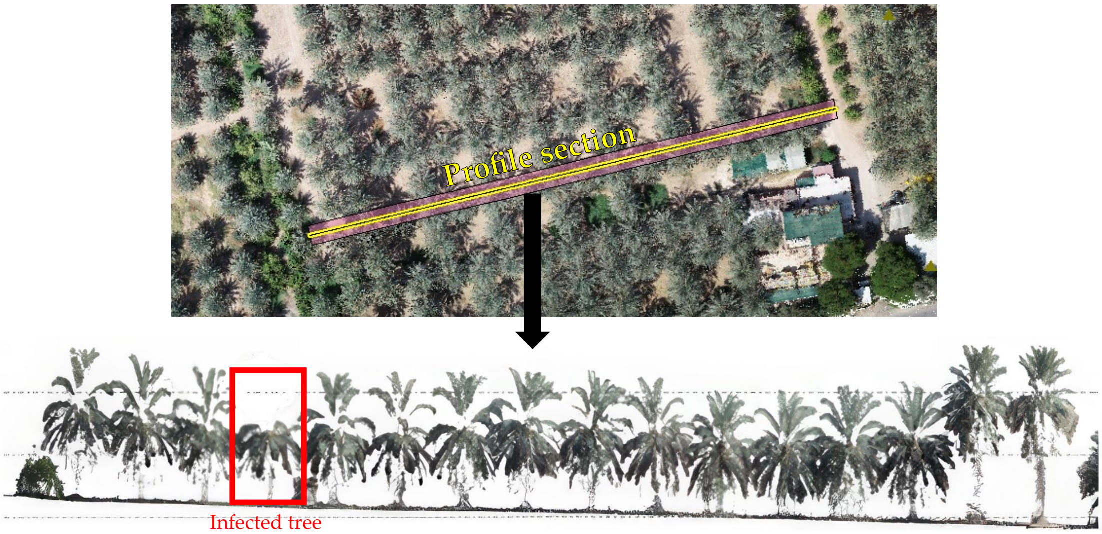

Figure 5. A profile section taken from a LiDAR point cloud of a palm tree farm shows a possible infected tree with missing fronds.

Table 5. Summary of papers from the literature on using remote sensing technology for palm tree monitoring.

Title/Concept	DOI	Sensors Used	VIs ML Techniques
Red Palm Weevil Detection in Date Palm Using Temporal UAV Imagery	10.3390/rs15051380	UAV, multispectral camera	NDVI, SAVI Deep learning, CNN
Use of Drones and Satellite Images to Assess the Health of Date Palm Trees	10.1109/IGARSS39084.2020.9324065	UAV, satellite imagery	NDVI, EVI
Relationship of Date Palm Tree Density to Dubas Bug Infestation in Omani Orchards	10.3390/agriculture8050064	Satellite, 8 band images	NDVI, GNDVI random forest
Unmanned aerial vehicles (UAV) utilization for mapping the health of oil palm plants	10.3390/rs14030799	UAV, hyperspectral camera	ML, random forest,
Efficient Framework for Palm Tree Dubas Bug Detection Using Satellite Images	10.3390/su151914045	Satellite RGB, NIR images	Deep learning, CNN
Use of Drones and Satellite Images to Assess the Health of Date Palm Trees	10.1109/IGARSS39084.2020.9324065	UAV, Satellite, RGB, multispectral camera	NDVI, GIS analysis
Seismic sensor-based management of the red palm weevil in date palm plantations	10.1002/ps.7836	Seismic sensors, IOTree	None
Detection of Palm Tree Pests Using Thermal Imaging: A Review	10.1007/978-3-030-02357-7_12	UAV, thermal	LWP, CWSI
Identification of Damaged Date Palm Tree in a Farm using IoT-based Thermal Image Analysis	10.1109/CITS58301.2023.10188730	UAV, thermal camera	ML, SVM
Efficient Framework for Palm Tree Detection in UAV Images	10.1109/JSTARS.2014.2331425	UAV, RGB	Extreme learning machine (ELM) classifier
UAV Derived NDVI Vegetation Index and Crown Projection Area (CPA) To Detect Health Conditions of Oil Palm Trees	10.5194/isprs-archives-XLII-4-W16-611-2019	UAV, RGB, multispectral camera	NDVI
Large-Scale Date Palm Tree Segmentation from Multiscale UAV-Based and Aerial Images Using Deep Vision Transformers	10.3390/drones7020093.	UAV, satellite RGB images	Deep learning VT, CNN
High-Resolution Multisensor Remote Sensing to Support Date Palm Farm Management	10.3390/agriculture9020026	Aerial sensor, hyperspectral, thermal, RGB, LiDAR	NDVI, REP, statistical analysis
Red Palm Weevil Detection in Date Palm Using Temporal UAV Imagery	10.3390/rs15051380	UAV, RGB, multispectral, thermal cameras	NDRE, CHM, gNDVI
Drones applications for smart cities: Monitoring palm trees and street lights	10.1515/geo-2022-0447	UAV, multispectral camera	NDVI
Physical and Physiological Monitoring on Red Palm Weevil-Infested Oil Palms	10.3390/insects14110859	General	General

4. Machine and Deep Learning for Disease and Pest Detection in Palm Trees

Machine learning (ML) and deep learning (DL) techniques have revolutionized the analysis of remote sensing data. These advanced algorithms can process large datasets, identify patterns, and make predictions with high accuracy, significantly enhancing traditional remote sensing methods.

Previous sections focused primarily on remote sensing technologies specific to palm trees while this section presents ML and DL applications. While the references mentioned in this section are initially developed for other crops or different types of palm trees, they provide valuable insights and can be effectively adapted for disease and pest detection in date palm trees.

ML algorithms, such as support vector machines (SVM), random forest (RF), and k-nearest neighbors (k-NN), have been widely used to classify healthy and infested palm trees based on spectral, thermal, and structural data [16,17,127,128]. These algorithms can handle the complex and high-dimensional nature of remote sensing data, improving the detection of subtle changes in tree health that may be indicative of pest or disease presence.

DL, particularly convolutional neural networks (CNNs), has shown even greater promise due to its ability to automatically extract relevant features from raw data without manual feature engineering. CNNs have been successfully applied to hyperspectral and multispectral data for detecting diseases like RPW infestation, with studies reporting high classification accuracies [45,97,129]. The depth and complexity of CNNs enable them to capture intricate patterns and relationships within the data, making them highly effective for pest and disease detection.

For example, Kuswidiyanto, et al. [45] used deep learning on hyperspectral images to diagnose plant diseases, achieving significant improvements in detection accuracy compared to traditional methods. Similarly, [17] applied SVM to hyperspectral reflectance data for early detection and classification of plant diseases, demonstrating the potential of ML in enhancing disease management. Mohanty, et al. [130] determined that DL models trained on large public datasets can accurately identify 14 crop species and 26 diseases, paving the way for close-range smartphone images for crop disease diagnosis on a global scale.

Integrating ML techniques with multi-sensor data further enhances their efficacy. By combining spectral, thermal, and structural data, these algorithms can leverage the strengths of each sensor type, leading to more accurate and reliable predictions. For instance, Easterday, et al. [50] demonstrated the effectiveness of using UAV-based multispectral and thermal imagery analyzed with machine learning to monitor water stress and disease in crops, highlighting the potential for similar applications in palm tree monitoring. Albattah, et al. [131] found that a drone-based deep learning approach using an improved EfficientNetV2-B4 achieves very high accuracy in detecting and categorizing crop leaf diseases, outperforming other recent techniques, and reducing time complexity. Furthermore, Marrs, et al. [132] found that combining LiDAR and hyperspectral data improves classification accuracy for tree species, suggesting that multi-sensor data provides richer information. While Albattah, et al. [131,132] focus on crop leaves and trees, the methodology can be directly applicable to palm tree health monitoring where palm tree diseases can be effectively detected and categorized using deep learning techniques.

The adoption of these advanced analytical techniques also facilitates the development of automated monitoring systems, reducing the need for manual inspections and enabling real-time detection and response to pest and disease outbreaks. This not only improves the efficiency of agricultural practices but also contributes to sustainable pest and disease management by enabling precise and targeted interventions.

In the following, some useful literature that discussed the use of machine learning or deep learning techniques for crop monitoring and management using remote sensing were identified. While these studies focus on crops beyond palm trees, they provide foundational insights into how similar technologies can be adapted for palm tree pest and disease management. For example, Sishodia, et al. [1] presented a review covering the applications of remote sensing in precision agriculture, including the use of machine learning techniques for various crop monitoring tasks. In a review paper, Zhang et al. [9] discussed the application of remote sensing technologies, including ML, for the monitoring of plant diseases and pests. Similarly, [14] reviewed the achievements and challenges of remote sensing in agriculture, highlighting the role of ML in enhancing crop monitoring and management. The study by Rumpf, et al. [17] demonstrated the use of SVM for the early detection and classification of plant diseases using hyperspectral reflectance data. Sharifi [19] focused on yield prediction using ML algorithms in conjunction with satellite imagery. Candiago, et al. [20] evaluated the use of multispectral images and vegetation indices from UAVs for precision farming, including the application of ML techniques. Zhou, et al. [21] used machine learning to predict rice grain yield from multi-temporal vegetation indices obtained from UAV-based multispectral and digital imagery. Chivasa, et al. [133] applied UAV-based multispectral data with a Random Forest classifier to accurately classify maize varieties into resistant, moderately resistant, and susceptible groups under artificial maize streak virus injection. Kuswidiyanto, et al. [45] focused on the use of DL techniques for plant disease diagnosis using aerial hyperspectral images, and Albattah et al. [131] presented an AI-based drone system utilizing DL (CNN) for multiclass plant disease detection. Table 6 provides selected references on crop health and pest monitoring using ML and DL techniques that can be adopted for palm trees as well.

Table 6. Selected literature discussed the use of AI-based techniques on remote sensing data for crop monitoring.

	AI Technique	Application	Reference
Machine Learning	Support Vector Machines (SVM)	Classify healthy and infested palm trees	Rumpf, Mahlein, et al. [17]
	Random Forest (RF)	Detect disease stress in crops	Chivasa, et al. [133]
	k-Nearest Neighbors (k-NN)	Classify healthy and infested palm trees	Rumpf, Mahlein, et al. [17]
	Integrating ML with Multi-Sensor Data	Monitor water stress and disease in crops	Easterday, Kislik, et al. [50]
Deep Learning	Convolutional Neural Networks (CNNs)	Detecting diseases like Red Palm Weevil infestation	Kuswidiyanto, Noh, et al. [45]
	Improved EfficientNetV2-B4	Detecting and categorizing crop leaf diseases	Albattah, Javed, et al. [131]
	Combining LiDAR and Hyperspectral Data	Improves classification accuracy for tree species	Marrs and Ni-Meister [132]
	Deep Learning on Hyperspectral Images	Diagnose plant diseases	Kuswidiyanto, Noh, et al. [45]
	Deep Learning on Public Datasets	Identify 14 crop species and 26 diseases	Mohanty, Hughes, et al. [130]

5. Conclusions

The overall analysis of remote sensing technology for identifying pests and diseases in palm trees emphasizes significant advancements and methodologies that improve the monitoring and management of agriculture. This is made possible through multispectral and hyperspectral sensors which use indices such as NDVI, NDRE, PRI, chlorophyll fluorescence, etc. to provide important information about the physiological condition of palm trees. Thermal sensors offer critical data on plant stress and water status using indices such as LST and CWSI. Detailed structural analysis input comes from LiDAR sensors by measuring canopy height, volume, and LAI.

Despite the capabilities of these technologies, each type of sensor has its limitations. RGB vegetation indices cannot accurately distinguish between infested and non-infested trees in most cases. On the other hand, multispectral and hyperspectral indices can identify changes in plant health but may require advanced analytic techniques or machine learning methods for precise interpretation. Combining spectral information with LiDAR's structural data is essential for comprehensive pest and disease monitoring.

Machine learning and deep learning- approaches have proven effective in enhancing the accuracy and reliability of pest and disease detection. However, integrating these into operational agricultural practices remains a major challenge that needs further research and development.

Future studies should consider increasing the emphasis on the development of UAV systems that are low-cost, optimization of algorithmic data acquisition and processing, and integration of multi-sensor data fusion techniques to enhance detection accuracy and operational efficiency. Moreover, advancing machine learning models for the automated interpretation of complex datasets and real-time monitoring capabilities will be essential. Future opportunities for emerging technologies, especially Internet of Things (IoT) technologies or edge computing for remote sensing applications in palm tree sciences, also offer promising opportunities for research. Furthermore, a promising line that could be pursued is the application of chemical mapping techniques in remote sensing. This new technology involves the detection and mapping of chemical substances, one of which is volatile organic compounds (VOCs) that are emitted by stressed plants. UAV sensors and satellite data can be employed to monitor the chemical emissions that reflect biotic stress, which can be considered as an additional data layer for early pest and disease detection. Although the current review has not focused extensively on chemical mapping, it offers exciting prospects for enhancing the precision of pest and disease monitoring in palm tree plantations. Future research will be able to determine the possibility of using chemical mapping in combination with remote sensing techniques that are already in use as a more complete solution; thus, more innovations in the field are to be expected.

In conclusion, UAV remote sensing technologies provide a powerful toolkit for palm tree health monitoring, their successful application requires a multi-sensor approach supported by advanced data analytics methods. Subsequent studies will need to refine these technologies to incorporate them within practical pest and disease management systems, thereby boosting sustainable palm tree agriculture productivity levels.

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