Hindawi
Journal of Sensors
Volume 2022, Article ID 5385505, 18 pages
https://doi.org/10.1155/2022/5385505

Review Article

Application and Potential of Drone Technology in Oil Palm Plantation: Potential and Limitations

Zailani Khuzaimah,[1] **Nazmi Mat Nawi**,[1] **Siti Nooradzah Adam**,[1] **Bahareh Kalantar**,[2] **Okoli Jude Emeka**,[3] **and Naonori Ueda**[2]

[1]*Institute of Plantation Studies, Universiti Putra Malaysia, 43400 Selangor Darul Ehsan, Malaysia*
[2]*RIKEN Center of Advanced Intelligence Project, The Goal-Oriented Technology Research Group, Disaster Resilience Science Team, Tokyo, Japan*
[3]*Department of Civil Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang 43400, Malaysia*

Correspondence should be addressed to Bahareh Kalantar; bahareh.kalantar@riken.jp

Received 3 September 2021; Accepted 1 August 2022; Published 1 September 2022

Academic Editor: Davide Palumbo

Oil palm has become one of the largest plantation industries in Malaysia, but the constraints in terms of manpower and time to monitor the development of this industry have caused many losses in terms of time and expense of oil palm plantation management. The introduction to the use of drone technology will help oil palm industry operators increase the effectiveness in the management of oil palm cultivation and production. In addition, knowledge gaps on drone technology were identified, and suggestions for further improvement could be implemented. Therefore, this study reviews the application and potential of drone technology in oil palm plantation, and the limitation and potential of the methods will be discussed.

1. Introduction

Oil palm has become one of the country's main sources of income apart from rubber and paddy cultivation. It has also dominated the world's vegetable oil producers such as soybean, rapeseed, and sunflower by more than 35%. At the present time, Malaysia and Indonesia have become the world's leading oil palm growing countries [1]. Furthermore, Malaysia has become the second largest exporter of palm oil and its related products. In 2020, Malaysia's palm oil production was projected to reach about 20 million tonnes (350,000 barrels per day) with total export revenue about RM72.30 billion. In terms of planting, oil palm is suitable for planting in areas that have sunlight between 5 and 7 hours every day. They required temperature as above as 18 Celsius with an optimum temperature between 28 and 32 Celsius [2], while the optimal rainfall distribution is between 2000 nm and 3000 nm [3].

However, an increase in demand requires more modern approaches and technologies to be adopted in a sustainable manner to increase the production. The development of information and communication technology (ICT), especially the Internet of things (IoT) including drone technology which provides mapping and data analysis services, can provide more accurate and effective information for precision agriculture technology. In general, IoT technology, especially drones, can collect and process information obtained from various sources and can help in collecting weather information, soil profile, and drainage, and at the same time, manage all crops in a more efficient way [4–7]. In plantation, drone technology is being utilized to monitor large plantation area due to its success in photography, aerial mapping, and surveillance [8, 9].

Drone which is also known as unmanned aerial vehicle (UAV) is an aircraft that has no human pilot on board to navigate the vehicle [10, 11]. Despite not having a pilot, it still can fly thousands of kilometers, into confined space, and fly remotely and autonomously [12]. It can carry lethal or nonlethal payloads [13]. Drone technologist classified drones based on its aerial platform. There are four major types of drones such as multirotor [14–19], fixed-wing [20–22] single rotor helicopter [23], and fixed-wing hybrid VTOL (vertical take-off and landing) [24]. Drones were first made by the Austrians in 1849 using explosive-filled balloons for military use which has been well known for nearly 150 years [25].

The first civilian drone was produced in the 80s in Japan at the request of the Minister of Agriculture, Forestry, and Fisheries [26]. The difference between civilian and military drones can be seen in terms of the size of the engine and its capability where civilian drones are powered by electric motors while military drones are powered by internal combustion engines. Most public drones are used for mapping and imaging [27].

Drones with specialized sensors (Figure 1), or drones that work in tandem with IoT, can record high-resolution photographs and help monitor a variety of vegetation properties. Aside from that, many sensors might be used in the agricultural sector [28]. However, the selection of type of sensors to be incorporated into the drone or UAV highly depends on the low payload capacity and the usage of minor platforms. Commonly, the main criteria that a sensor must meet to capture high resolution image are an acceptable weight with appropriate size and to utilize enough energy. In addition, different types of sensors can monitor specific parameters such as the color and texture of vegetation and the geometric outline of agriculture crops. Furthermore, certain sensors can monitor plant biomass, vegetation health, and other critical agricultural properties at various phases of plant development. This data can also be utilized to monitor utilizing certain wavelengths of radiation [29].

The function of each sensor is depending on the function of its thermal sensor to obtain data on the relative temperature of a surface and is widely used for the purpose of designing irrigation and drainage systems in the plantation sector. Multispectral sensors are usually used to produce normalized difference vegetation index (NDVI) images that help to distinguish between cultivated areas and vacant land [30]. It can also detect crops that are under pressure by obtaining data on plant fertility levels. On the other hand, hyperspectral sensors have several hundred bands that are commonly used to obtain and process information from the electromagnetic spectrum in each pixel of the image taken. However, for light detection and ranging (LiDAR) sensor, it was usually utilized to obtain the slope elevation and structural data [31].

This article was written to highlight an overview of the use of drones' technology in the oil palm industry its weaknesses and recommend further research to enhance the capabilities of more effective drone technology in the oil palm industry. The following section reviewed a list of drone applications in a wide range of oil palm management and monitoring, accompanied by its lapses or gaps and recommendation for improvement of the drone technology in the oil palm industry.

2. Drone Capabilities: Endurance and Range

Drone configurations and features are varying according to the platform and mission requirements. There are various classifications for drones that focus on different parameters that can be found in the literature reported by Hassanalian and Abdelkefi [36]. The advantages of each drone always depend on the user demand. For instance, in scientific research, the drone was classified based on characteristics such as size, duration, range, and durability [37]. According to Arjomandi [38], drones are also classified according to weight, flight distance, wingspan, maximum altitude, and engine capability. For example, heavy drones are for those over 2000 kg, heavy with a weight between 200 kg and 2000 kg, medium with a weight between 50 kg and 200 kg, and light (5 kg-50 kg) and minidrones with weight less than 5 kg as shown in Table 1.

Drone endurance is described as the total duration during take-off. For an electric fixed-wing helicopter or quadrotor, this is primarily associated with the battery's capacity as well as the ability of the motor to produce current to keep the helicopter on air. There are several factors that can be used to determine the endurance; however, a simple endurance computation can be estimated using the below equation [39].

$$\text{Endurance (hrs)} = \frac{\text{Battery Capacity (Ah)}}{\text{Current (Amps)}}. \tag{1}$$

The endurance of the helicopter depends largely on its size, weight, and the weight of the payload. For instance, a macrofixed-wing aircraft with a large wingspan will have longer endurance compared to a miniquadrotor. Another key point is that the endurance also will have a factor on the range of the aircraft. The distance with an uncrewed aerial vehicle can go is known as its range. Furthermore, the range of the aircraft is dependent on the amount of current that is being applied for the aircraft to be lifted, the endurance itself, flight speed, and the aerodynamic performance which can be determined by using the range of a drone. Meanwhile, the range can be calculated by calculating the fixed-wing and quadrotor by the equation below [39].

$$\text{Range (miles)} = \frac{\text{kV.V.60.Pitch}}{12.5260}\,\text{Endurance (hrs)}, \tag{2}$$

where kV is the amount of revolutions per minute, the motor will turn when 1 V was applied to the motor, pitch is the pitch (in inches) of the propeller on the UAV, and the endurance is the amount of time in hours the aircraft can stay in the air.

This equation will enable a rough calculation of the total UAV's range. However, to effectively estimate the range, factors like wing area, weight, and the coefficient of lifting of the air foil used on the helicopter will be crucial.

3. Application of Drone in Oil Palm Plantation

Malaysia is the world's second largest exporter after Indonesia with about 5.08 million ha of oil palm plantations. Most of the plantations are owned by private farmers who work on a small scale [41]. They desperately need an autonomous platform with an affordable price for the use of monitoring, inventory, crop yield assessment, spraying, health assessment, and disease detection. The capability of drone technology in

(a) (b)

(c) (d)

Figure 1: Examples of sensors used by UAVs for PA: (a) thermal sensor [32], (b) RGB sensor [33], (c) multispectral sensor [34], and (d) hyperspectral sensor [35].

Table 1: The proposed drones' categorization by [38] based on their weight.

Designation	Weight range
Extremely heavy	> 2000 kg
Heavy	200 kg ≤ 2000 kg
Medium	>50 kg ≤ 200 kg
Light	>5 kg ≤ 50 kg
Mikro	≤ 5 kg

taking high-resolution aerial photographs has changed the way oil palm cultivation into more economical [42]. Conventional methods have been replaced with the use of drone technology [43, 44] that can provide more quick and accurate information to help in making smart decisions. Drone technology which is an emerging technology is capable of providing significant functions in precision agriculture and smart farming, to enable the increases in long-term production [45] by the acquisition of real-time environmental data. Drone is one of the breakthroughs for smart and precision agriculture farming, which is utilized for monitoring vast and cultivated lands and provides practical solutions for precision farming [5, 29]. With that, the main purpose of precision farming to optimize yields and maintain sustainable crop production capacity based on crop monitoring and crop health assessment [44] can be effectively achieved.

By recording high spatial and temporal resolution photos, drone can be vastly utilized in a wide range of applications, including crop management. Through photographs, it can intelligently, simply, and cost-effectively monitor crop and vegetation factors. UAVs for crop monitoring and management will provide opportunities for the farmers to monitor, map, and survey a diverse range of crops, located in many countries around the world [46]. Recently, globally, many have been considering using drone for agriculture purposes for crop irrigation [47] and growth for yield estimation, health determination, disease detection [47], and for spraying [48].

Drone technology has bridged the gap between ground base observation and satellite data, and it has increased its capabilities in terms of crop monitoring, yield mapping, soil profile and soil property mapping, crop health, and disease monitoring and spraying [40]. This technology is easy-to-operate, flexible, and in addition, low-cost drone has greatly revolutionized smart farming technology from the beginning of the planting process up to the harvesting. Drones can also provide live data from various types of sensors as shown in Figure 2 (multispectral, near infrared reflectance (NIR), LiDAR etc.), with high resolutions imagery up to less than one centimeter per pixel. With this information, it can help a lot in replanting planning, oil palm data census for inventory data, calculation of land use, distance between crops, canopy size, oil palm height, and crop density. With all the data and information, it is very useful in the development of support systems in decision-making and estimating plantation management-based results. Figure 3 suggests the suitability of each sensor usage at various stages of cultivation in order to obtain relevant data and information, and Table 2 shows summary of drone application in plantation.

3.1. Oil Palm Plantation Inventory. In most underdeveloped countries, land registration is a big problem such as in Malaysia. Failures in land registration caused many difficulties such as title disputes, control, and distribution of aid such as pesticides and fertilizers. Land registration in the form of terrestrial measurements is projected to be addressed in the next decades. For urban planners, monitoring urban development has become a vital issue. Drone technology is an alternative step to speed both processes because it is a unique instrument that can fly without a human operator on board and conduct sophisticated and viable duties such as monitoring, cadastre, and earthwork analysis. The photogrammetry method used in drone is to obtain an ortho map.

3D mapping is an integral part of geological surveying [61]. Recently, drone usage for visual surveying through the generation of 3D images of sites has become a necessity [62]. Drone's technologies can acquire high-resolution images converted into 3D surface models used for topographic mapping, volumetric calculations, or showing the site in the 3D format [63].

Drone technology for the oil palm plantation industry includes all relevant information, including crop density, drainage, crop area, and basic infrastructure information such as plantation road network, and crop yield estimates. Figure 4 shows the images and information on the inventory using drone technology.

Drone is capable of capturing the crown formation of palm trees images by using high spatial resolution images. Here, it uses the template matching algorithms to detect the object's boundary of the image as a criteria [64]. In some instances, the problem of image distortion or occlusion can be overcome by using the method of object base analysis to reduce the influence of scale and geometry of objects through segmentation [56]. However, parameter selection will result in inaccurate detection in trees. To obtain the best inventory information, the use of satellite images with fine resolution is particularly suitable for large areas of oil palm [57].

Nevertheless, the limitations of satellite data such as frequency of public coverage, cost, and time make it less suitable for the estimation of structural parameters. In order to improve accessibility, low operating costs, and enhance usage, the development of lightweight drone platforms was developed as an effective mechanism in oil palm plantation management. For this development, the UAV teams had been established by major commercial oil palm companies for a routine acquisition of aerial imagery [65].

3.2. Tree Counting. Tree counting is vital for estimation of yield, observation, replanting, and layout preparation. Nevertheless, it is costly, labor-intensive, and prone to human error when done in the field. Furthermore, due to the variability of the plantations, most plantations used to estimate cost estimates by multiplication of the total location by the amount of palms per hectare, which is inaccurate because of the diverse land mass such as hilly, undulating, or flat and presents of natural features such as river, land, or forest. Remote sensing was a possible option for seeing the plantation area and automatically counting the trees to solve this problem.

In the mid-1980s, studies into automatic detection of trees and feature extraction from digital imagery began. Pinz [66] offered aerial imaging utilizing a vision expert system; although, various detection methods have been proposed. This system powers the centrifuge. The center of the tree crown was successfully detected using this approach, and the radius was estimated using local brightness, followed by the valleys between the tree crowns using ground sampled distance digital aerial images.

Individual trees, on the other hand, were detected using software. To distinguish individual trees, Woodham and Pollock [67] use model-based template matching approaches. Kattenborn et al. [59] proposed a method for automatically detecting single palm trees using photogrammetric point clouds (Figure 5).

VisualSFM was used to process single camera images with a structure from a motion tool chain. Each image was divided into three categories: palms, shrubs/trees, and the ground. A multiscale dimensionality criterion were utilized to train and evaluate the data set for classification purposes, in which the classifier was set in a separate scale factor. Palm trees and their ground soil were classified using point cloud local dimensionality features. Algorithms are limited while training a classifier for a dataset. Because training a classifier takes time and requires more computer resources for each

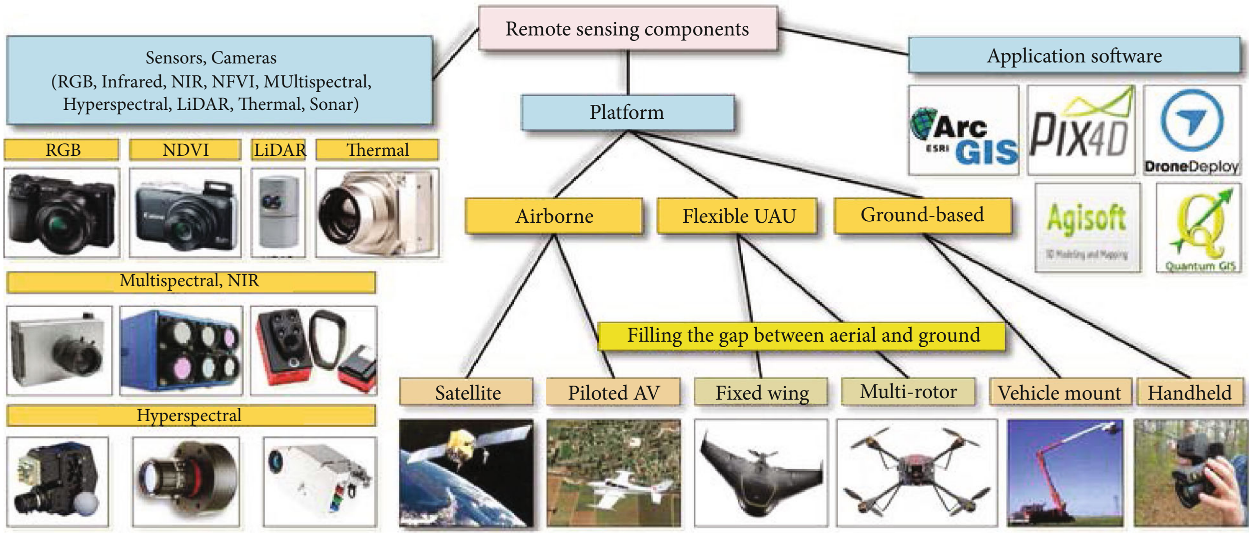

Figure 2: Typical components of a UAV-based remote sensing platform for precision agriculture in oil palm [40].

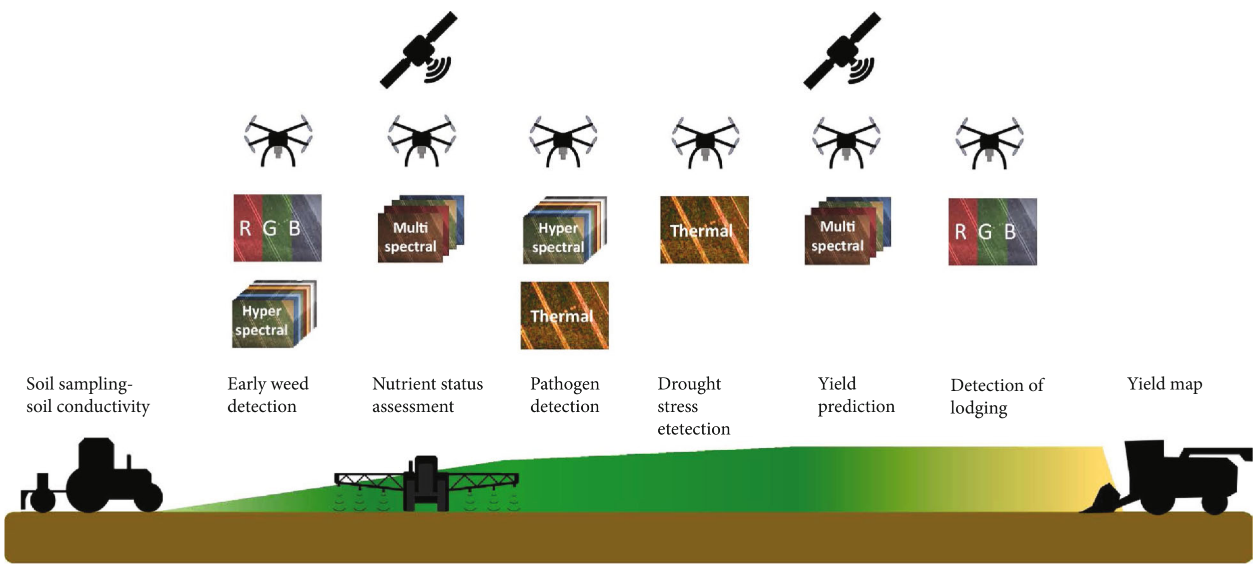

Figure 3: Schematic overview showed the different ways to extract spatial information in the areas, the useful platforms and the optimal UAV sensors, throughout a growing season of a crop. The optimal sensors for UAVs were also shown. Abbreviations: RGB: red-green–blue [60].

type of tree species, the classifier must be coached before detecting trees.

For this study, a structure from the motion toolchain with VisualSFM was used to process single-camera images. The images were classified into three classes: palm, shrubs/trees, and ground. For classification, a multiscale dimensionality criterion was used whereby the classifier was set to a different scale factor that trained and tested the data set. Local dimensionality characteristics of point clouds were applied to classify palm trees and their ground soil. Training a classifier for a dataset leads to a constraint for algorithms. Since training a classifier is time-consuming and needs more computational power for each tree species, one must coach the classifier before detecting trees.

Mansur et al. [68] utilized drone data capture and spatial filtering to acquire data for counting oil palm tree using ground control points. They used the concept of crown geometry and vegetation response to radiation in their research. A spatial convolution processing approach, such as a low pass filter, was used to detect the tree crown in the enlarged image. After applying a spatial filter to the data set, morphological analysis was used to perform object extraction, image filtering, and image segmentation processes.

Wang et al. [69] improved on Brandtberg and Walter [70] work by first using edge detection methods to detect the boundaries of tree crowns, then intersecting the results of local nonmaximum suppression on grey level images and local maximum values of morphological transformed

Table 2: Summary of drone application in plantation.

Literature work	Objective	Task	Technical characteristics and payload
[49] [50]	To detect the drainage pipe	For a monitoring purposes	VIS-C, MS, and TIR camera
[51]	To monitor the vegetation level	For a monitoring purposes	Camera GNSS IMU LiDAR Multispectral
[52]	Monitoring vegetation state	For a monitoring purposes	Camera Compass First person view platform FlightCTRL GPS system GSM modem Magnetic Multispectral NaviCtTRL
[53]	Evaluation water stress	For a monitoring purposes	3-axis accelerometer 8 GPS system Digital compass FlightCtrl NaviCtrl Pressure sensor Storing device Thermal sensor
[54]	Monitoring vegetation state	For a monitoring purposes	IMU LiDAR Multispectral sensor Single-board computer
[55]	Spraying with consideration of climate conditions	For a spraying process	Spraying device
[56]	Spraying fruits and trees	For a spraying process	Barometer IMU Magnetometer Multispectral sensor Servos Spraying device
[57]	Estimating chlorophyll density	For a monitoring purposes	Autonomous power supply Control switches GPS system Hyperspectral sensor LCD screen Storing device
[58]	Oil palm harvest prediction	For a data acquisition	20.2 mega pixel digital camera
[59]	Palm tree detection	For a data acquisition	Panasonic Lumix G3 with a 20 mm lens

distance between pixels. By combining the two methods, a decent estimate of the treetops was obtained, which were subsequently tallied using contour-based methods. The presence of background objects, such as buildings and roads, however, causes this method to fail.

3.3. Drone for Spraying. In the present era, various developments in precision agriculture are being carried out to increase the crop productivity. For example, in the developing countries like India, over 70% of the rural people who depends upon the agriculture fields need to be feed. However, their agriculture fields often face dramatic losses due to the plant diseases. These diseases either come from the pests or insets, which have possibilities to reduce the productivity of the crops. Pesticides and fertilizers were used to kill the insects and pests to enhance the crop quality. Hence, the WHO (World Health Organization) has estimated one million cases of ill caused by the pesticides spraying activity in the field. Therefore, precision agriculture to cater the growing population is so demanding. In precision agriculture, the drone's technology is being utilized to spray the pesticides to avoid the health problems of the users when they spray manually. Drones can be operated easily for this purpose [71]. This system was first developed in Japan in the 1980s, by the combination of unmanned aircraft with small pesticide tanks [72]. Today's drones were developed to be able to lift big tanks with up to 10 liters of capacity. Furthermore, the rate of liquid discharge could be set to

Figure 4: Mapping and inventory of oil palm plantation tree counting analysis [40].

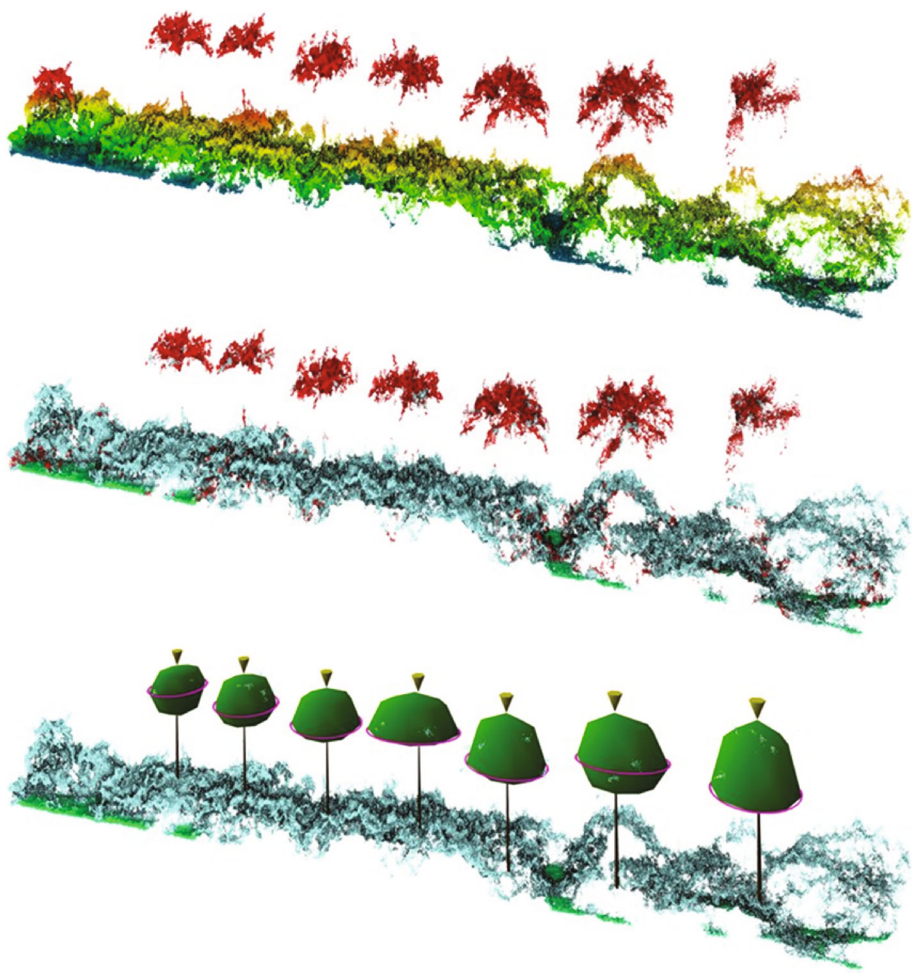

Figure 5: Automatic single palm tree detection using photogrammetric point clouds [59]. Palm: red; other vegetation: blue; ground: green (center) with modeled palms (bottom). Green shapes represent the convex hull of the crown, vertically surrounded by crown margins (purple). Yellow cones represent the top (z) and the position (x, y).

one liter per minute that makes it possible to cover a large area in 10 minutes. Also, drone-based spraying platform integrated with an aerial crop monitoring process will be able to provide efficient and accurate use of the agrochemical products. This will reduce the number of agrochemical products usage and is also a part of environmental protections. According to Zhang et al. [73], drones using M-18B and Thrust 510G model can fly at heights of five meters and four meters, respectively. He found that height differences had a significant effect for effective and uniformity spray on crops. Meanwhile, Kurkute et al. [74] used a quadcopter (4 rotor drone), which uses a universal spraying mechanism to spray liquid and solid contents. The author reported different control systems for agricultural purposes

Figure 6: Drone for crop spraying [76].

and found that the Atmega 644PA model is the most suitable and efficient drone. Meanwhile, Sadhana et al. [75] used a different approach in developing drone modules for simpler pesticide spraying mechanisms in improving yields as well as crop protection. By using a quadcopter drone, the author identified it that it was able to carry a load of 1 kg and use to spray pesticides at a height as shown in Figure 6. In this study, the author detected that the quadcopter drone was operated by Arduino UNO AT mega328 system and brushless direct current (BLDC), electronic speed control (ESC), MPU-6050 consisting of MEMS accelerometer, and MEMS gyro in one chip, radio receiver, and LiPo battery.

Kedari et al. [77], also used quadcopter drones that is suitable for indoor and outdoor crops. It is an autonomous flight that sprays pesticides as well as fertilizers using Android devices as well as Bluetooth that operates in real time. It can be used in agricultural sectors to reduce the time and the hazardous effects that can present during spraying of pesticides and fertilizers.

3.4. Biomass Estimation. A major requirement for precision farming is to monitor biomass which is an important step throughout the oil palm tree life circle [5, 78]. However, due to the presence of natural influences, precision farming must be modeled to determine the level of nutrient supply, water availability, soil quality, and healthiness because these parameters will contribute to the oil palm biomass. In precision farming, an effective management of the oil palm biomass need to be considered. Modeling the yield of a field through a satellite image by stratification often turns out to be mostly outdated, too cloudy, and not available for specific dates as of when needed. Another downside of the method is in field measurements, as it is hard to replicate and to cover wide plantation area that has too many plots. Besides that, it can hardly take care of small segment of the field apart from the cost and labor-intensive that is required for the whole process. Conclusively, it is an expensive venture that does not bring a perfect solution in biomass modeling. However, dynamic progression of drone systems enables to join airborne surveying with precision and resolution of terrestrial methods [63, 79, 80]. With this, drones became advantageous in biomass monitoring for oil palm modelling assessments via photos taken by consumer-grade RGB camera mounted on a small octocopter [81]. Further, some scholars use multispectral cameras, e.g., near-infrared in addition to RGB [82].

Tree geometric parameters from an orchard can also be estimated from data collected from the drone [83, 84]. By using an information collected from the drone, one acquired the crop parameters such as biomass that plays a significant part in yield forecast and in optimizing plantation management. Biomass can be assessed through spectral reflectance measurements [85] from space [86, 87] and from the air [88, 89]. Nevertheless, these measurements frequently consist of refined and costly apparatus that necessary for vigilant standardization. Drones occasionally denoted as remotely piloted aerial systems (RPAS) or unmanned aerial systems (UAS) actually are the evolving implements to be used for small-scale remote sensing [78, 89, 90]. UAVs can be used for oil palm biomass modeling, for instance, crop status investigation using near-infrared or thermal data. Figure 7 below shows the research methods that was summarized with reference to some previous research.

3.5. Crop Growth Monitoring and Yield Estimations. The combination of real-time remote sensing images and information from related sensors can provide information that can increase plantation productivity through the mapping of spatial information changes in the field. Information on the status of the cultivation area such as soil profile and crop fertility can help in fertilization planning, watering schedule, weather analysis data, and also crop yield estimates. The collection of all this information by using drone technology can provide a more effective management plan [86].

Bura et al. [58] used drone technology in predicting the yield of oil palm harvest, by dividing the study into two stages, namely, by the configuration of the drone system and in the image processing for predicting the yield of oil palm harvest. The drone system configuration included the use of an X-8 airframe with Pixhawk control system, electric motor, and 20.2 mega pixel digital camera RGB (red, green, and blue) sensor. High-resolution images were once taken at a 6-year-old oil palm plantation in North Sumatra. The resulting image was used to calculate the forecast of crop yield by using the number of crops. The estimated harvest for that particular area was detected as an average of 50.5 tonnes per hectare per year, which is more than the management company's estimation at 23 tonnes per hectare per year.

An accurate early yield prediction is beneficial to farmers as well as the plantation industry. With drone technology, the use of high-resolution sensors can map accurate crop information such as crop height, canopy cover, and crop distribution, which can be used to predict crop yields. Distribution using RGB sensors [92, 93] and multispectral sensors [94, 95] is used to predict crop yields.

Drones can be used to observe the crop with different indices. It can also cover large parcel of land in a single flight using either thermal or multispectral cameras [79, 96]. It will capture the reflectance of the vegetation canopy mounted beneath the quadcopter. The camera captures one image per second and records it in the memory and transferred

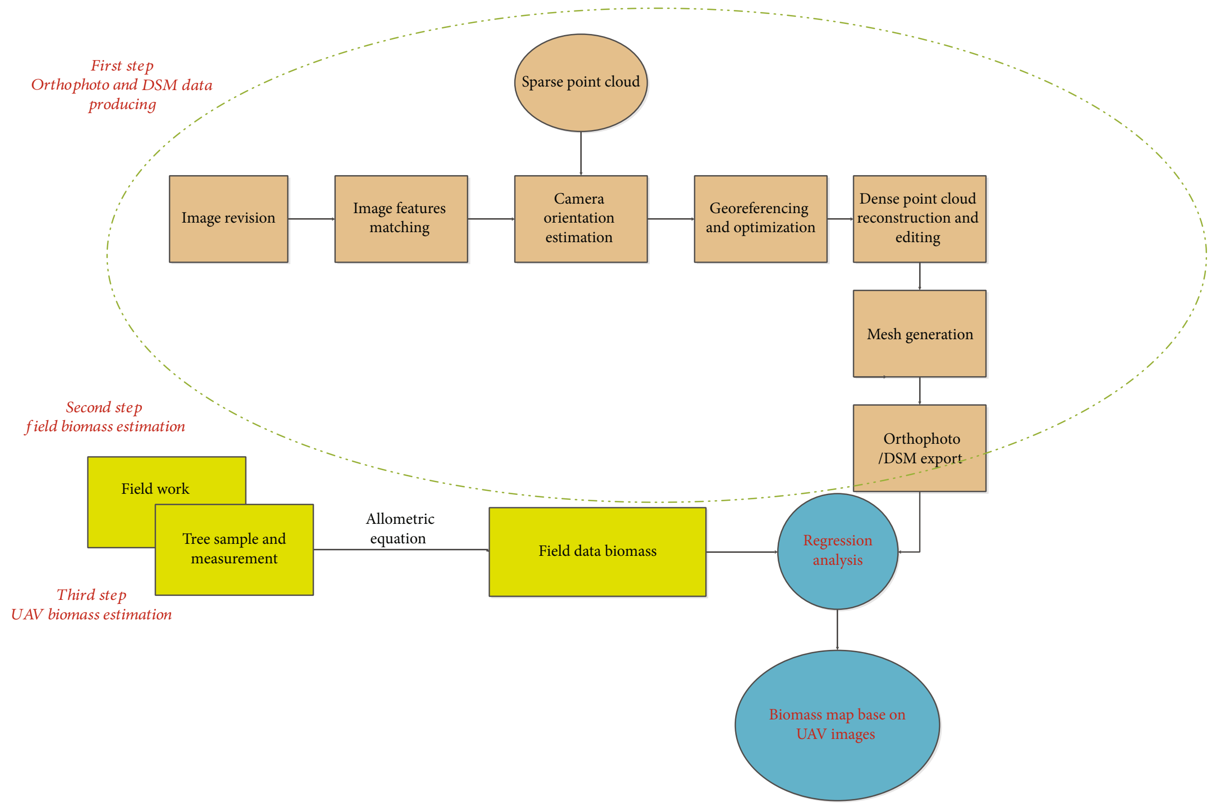

FIGURE 7: Biomass mapping flow chart.

to the ground station via wireless telemetry that uses MAVLINK protocol. The images were recorded in visible five brands with contradicting wave lengths, for example, blue wavelength 440-510 nm, (ii) green wavelength 520-590 nm, (iii) red-wavelength 630-685 nm, (iv) red-edge wavelength 690-730 nm, and (v) near-infrared wavelength 760-850 nm. The data retrieved from the multispectral camera through telemetry was analyzed using the geographic indicator NDVI [97–99] that was represented in the equation below.

$$\text{NDVI} = \frac{(R_{\text{NIR}} - R_{\text{RED}})}{(R_{\text{NIR}} + R_{\text{RED}})}, \tag{3}$$

where R_{NIR} represents the reflectance of the near-infrared band, and R_{RED} is the reflectance of the red band. A computation value of -1 to +1, or close to 0 (zero), means that there is no vegetation on the crop, and a value close to +1 (0.8 to 0.9) signifies that the highest density of green leaves was grown on the crops. For these results, farmers can effectively point out the spot to spray pesticides and fertilizer. The equipped GPS (Global Positioning System) module will manage the GPS coordinates of each acquired image. The GPS coordinates of the image are then saved in the UAV to pesticides or fertilizer spraying simultaneously without control.

There are various types of drone that were invented for agriculture purposes. Drones such as the DJI Agras MG-1 [100] were designed to apply liquid pesticides, fertilizers, and herbicides. On the other hand, multispectral and hyperspectral aerial and satellite imagery used to create NDVI maps will help differentiate the soil from grass or forest and detect plants under stress and differentiate between crops and plant growth stages. There are strong correlations between NDVI data measured at certain point with the crop yield and plant growth stages [101]. Hence, tracking the plant growth will help provide an accurate estimation of the crop yield and address any plant growth issues earlier. For the purpose of obtaining soil profile and plant fertility by using drones, suitable sensors used are multispectral, hyperspectral, and infrared sensors. Agricultural information with a combination of NDVI data with crop-water stress index (CWSI) and canopy-chlorophyll content index (CCCI) can provide more accurate results. The response of the plant leaf reflection to the sensor can provide information on the fertility level of the plant whether it is a state of dehydrate or stress (Figure 8). The information can also distinguish between cultivated areas and non-crops.

Forecasting plantation production is something that is important in this industry. Drone technology promises the accuracy of information obtained through the use of appropriate sensors in the collection of images and data such as RGB and multispectral sensors to estimate crop densities and biomass. Through appropriate analysis of the method, the accuracy of the yield estimation can be improved.

3.6. Crop Health Monitoring. In precision agriculture application, the most common technique to assess vegetation health is remote sensing techniques and image analytics. Meanwhile, one of the most widely used RS approach is

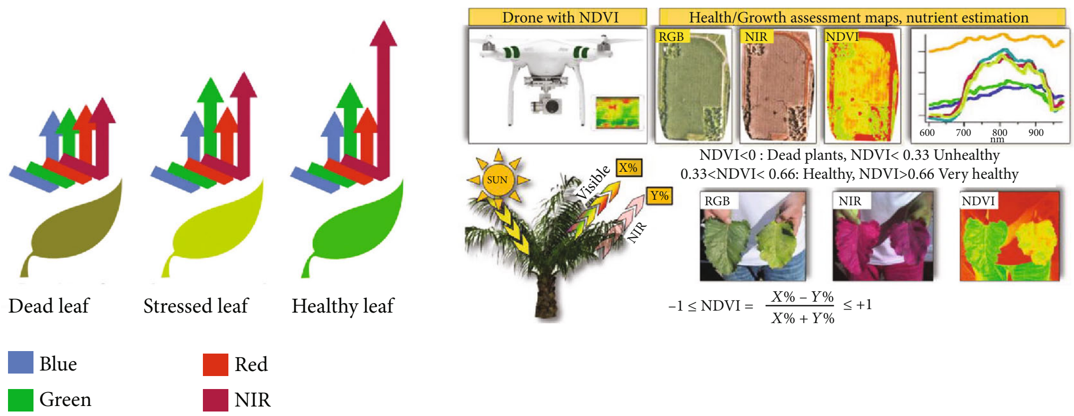

Figure 8: Normalized difference vegetation index.

aerial inspection, using satellite acquired imagery and manned aircrafts, as well as drones [102, 103]. In the context of precision agriculture, exploring satellite images is a big investment for a typical farmer, and sometimes, their quality and resolution are not acceptable and technical. However, conversely to previous cases, aerial photos acquired by manned aircrafts reveals a more acceptable quality compared to satellite images. On the other hand, drone is less cost-effective and can provide high-resolution images. Drone, an unmanned aircraft, will be operated remotely by an operator. It can carry several cameras such as multispectral and hyperspectral that acquire aerial photos. More so, these images will be used for the extraction of vegetation indices that allows farmers to inspect crop variability and stress conditions constantly.

Duan et al. [104] used the application of NDVI in monitoring plant growth. This NDVI technique calculated photosynthetic and assessing the canopy status of green plants. He used a multispectral sensor (RedEdge) at low flight altitudes to record images from various bands from various stages of plant growth with a transformation ratio measured between the reflectance measured at the red wavelength range and NIR wavelength range. With all the data obtained from multispectral sensors and field verification using handheld sensors (e.g., Green Seeker), this range of information had assisted in the development process of crop growth mechanisms.

Reinecke and Prinsloo et al. [97] were more focus in studying the capabilities and limitations of drones in maximizing crop yields and crop management. By using two drone camera technologies, namely, UVIRCO and Aerobic, his study concluded that many farmers invested in drone technology to improve their crop management capabilities. It is because his technology has the ability to produce digital maps that can provide crop information such as crop health, crop loss, irrigation system, and crop spraying.

Kerkech et al. [105] used a convolutional neural network (CNN) system and color information to detect plant health status. CNN used diverse color space with various crop indexes with a combination of the information analyzed using six methods: capture the image, divide the image into blocks, create two sliding window schemes, color conversion from RGB to HSV, and separate the intensity information chrominance by using LAB and YUV. The results were classified according to healthy plant, potentially diseased and diseased plant classes, mapping disease plant generation, postprocessing steps such as mathematical morphology, removal of small areas, contour detection, and overlapping disease maps on RGB images.

3.7. Pest and Disease Detection. The detection of pest and disease has become a significant concern in oil palm plantation. This is a result of timely detection of pest and disease that can be of help in prevention of an outbreak. The most common disease in the oil palm industry is caused by *Ganoderma boninensis*. This disease often causes huge losses in oil palm management. A fungal disease internally rots the oil palms trunk, and this makes it to be fundamentally vulnerable and collapse due to strong wind [106]. It is a highly contagious disease. However, in the early stage, the infected palms often show sign till it deteriorates. If the diseases invested oil palms can be identified earlier, it can be quarantine and remove properly to prevent the spread of this disease to other plants [107]. Using remote sensing and UAV imagery system, the status of palms can be assessed on the basis of the signs shown at given spots earlier, and the diseases or pest infestation can be diagnosed as soon as possible [108]. On the basis of research hypothesis, oil palm infected by Ganoderma will show noticeable signs at the beginning; therefore, several researches were carried out to remove the oil palms infected with Ganoderma from the plantation at the early phase of infection. The use of NIR cameras integrated in the UAV able implies the high reflectance of vegetation in the NIR region that is invisible to the human eye. This can be used to demonstrate the health of a particular plant. The RGB and NIR images coupled with geographic information system (GIS) analysis will be successfully used to monitor Ganoderma BSR in oil palm plantation.

Day by day, chemical usage is increasing, which has led to the environmental impact and health risk aspect on the user and has become crucial to be considered. Indeed, chemicals may threat the important inhabitants that live around the areas. Furthermore, pesticides are also being adopted by crop and natural resources like water and soil and result to some concealed substances in the food chain. This can also increase the risk for both livestock and humans. However,

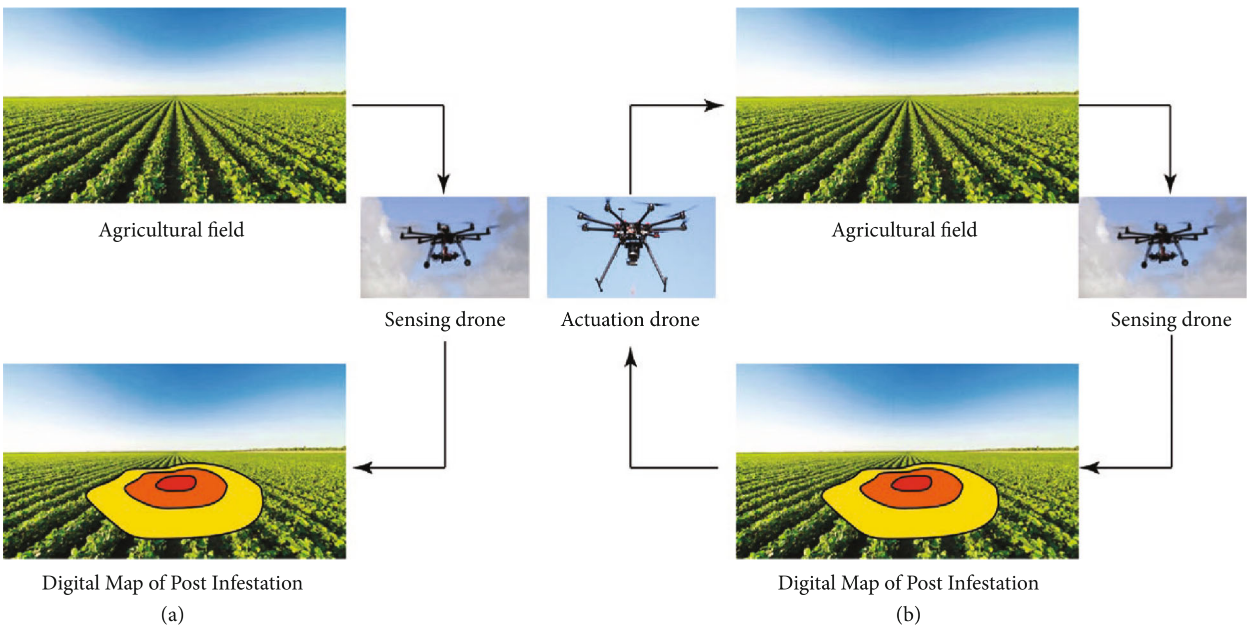

Figure 9: Drone used for detection of pest hotspots adapted from [37, 112].

by autonomous precision agriculture, these effects can be controlled. Additives, like fertilizer and pesticides, are sprayed when necessary, rather than being sprayed over a vast or specific area that crucially need will be identified beforehand through drones in agriculture. Many vegetation indexes involving several data characteristics such as the NDVI have been developed. Unique camera systems capable of acquiring data from an invisible part of the electromagnetic spectrum known as NIR and extract adequate information, which includes the presence of algae in the rivers or oil spills near costs, were developed [109]. Currently, drone usage has recently been introduced for big areas to inspect and target areas that need to be irrigated and fertilized [110]. This approach can be time saving for agronomists, water resources, and minimize chemical application. This type of farming method has the tendency to improve of crop production and quality. Specifically, lack of water, nutrient stress, or diseases can also be recorded and localized.

Furthermore, an object-based image analysis (OBIA) was performed to classified oil palms in a selected area into three categories such as healthy, moderately infected, and severely infected. These results showed that the OBIA can be used to analyzed multispectral images of oil palms to detect moderate and severe infection of Ganoderma disease. Izzudin et al. [111] stated that the Ganoderma disease severity index (GDSI) can be obtained from the aerial images of the infected oil palms. Through this, the detection of early infection of Ganoderma has become more feasible with an advanced algorithms and classifiers which incorporated with multispectral and hyperspectral aerial images application.

Detection of pest hotspots using drones is known as sensing drones, while drones used for precision distribution are known as actuation drones. Both types of drones could be used together to initiate a communication to establish a closed-loop (integrated pest management) IPM solution (Figure 9). Using drones in precision pest management are very cost-effective and reduce harm to the environment. Meanwhile, sensing drones could reduce the time required to scout for pests, while actuation drones could reduce the costs of dispensing natural enemies [37, 112].

3.8. Weed Mapping and Management. Biotic threats such as weeds, insects, bacteria, fungi, and viruses are major factors influencing crop quality and yield. Weed problems are the main threat causing huge losses in crop yields globally [113]. Weeds are the main competitors for crops in obtaining their nutrients [114], light [115], space [116], and water [117]. Besides that, the weeds' formation of toxic molecules and chemical signals will also interfere with crop development [118].

Drone technology is very suitable in weed detection, and the main advantage of drones in comparing to the conventional conditions in shorter time and optimal control of resistance on crops planted in rows [119] is to increase the effectiveness of drone usage for this purposes. In just a few minutes, a drone can be able to collect data covering several acres of area and provide images to detect the weed patches [120]. Later, those images will be processed using deep neural networks [121], convolutional neural networks, and OBIA [29, 60]. The final data will be concluded in three types of sensors such as RGB, multispectral, and hyperspectral sensors.

Weed infections in farm areas are usually uneven, and drone technology systems offer the best methods to map weeds and provide site-specific weed management (SSWM) methods. Two methods of weed detection are used, namely, the detection of spectral band differences between weeds and crops, and the second is the use of remote sensing data that is not from a multitemporal drone [122]. By using a drone application, the data obtained can be processed by supervised classification method only by using RGB sensors if the difference of the spectral signal is successfully identified

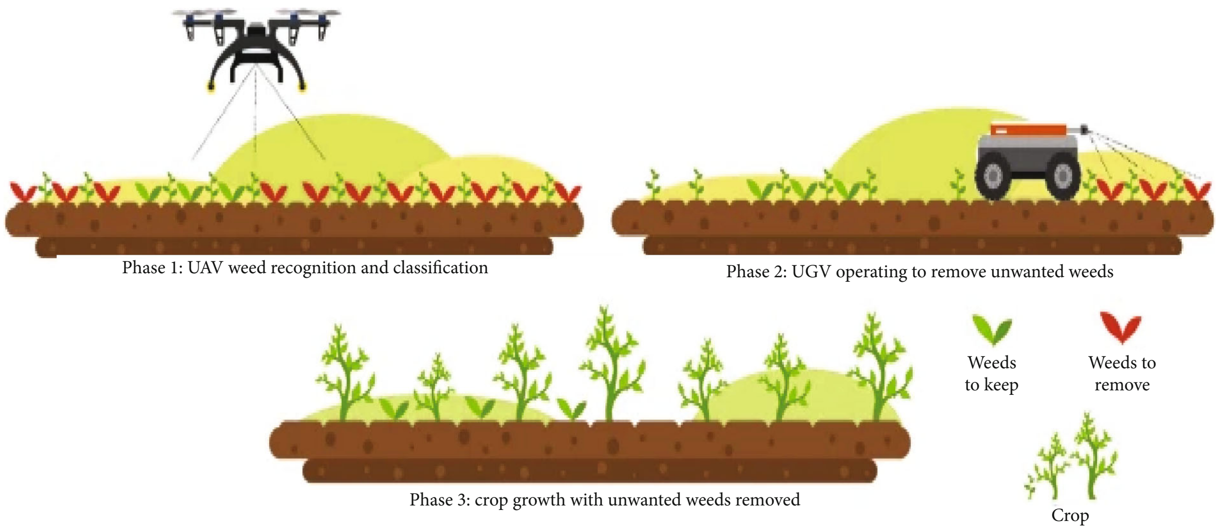

Figure 10: Weed management phase in a plantation system using drone technology [131].

between weeds and plants [123, 124] as it can produce a map that can pinpoint the location for herbicide spraying [125]. However, there is no guarantee that it can be fully resolved [126]; drone handling techniques and related tools such as accurate and fast field data support can help in effective solutions in a timely manner [127]. The second approach is for early monitoring at the beginning of the crop development using high-resolution images drones and a unique method called OBIA. This method analyzes nonpixel objects like the traditional method, and the RGB sensors are very suitable to use because their spatial resolution exceeds the spectral resolution [128]. Using the latest technology can save a lot of labor and time identifying weeds and their eradication methods [129, 130]. This drone technology has been shown to significantly reduce the use of poisons without affecting crop yields [122]. In the future, high-resolution hyperspectral with a combination of spectral discrimination and OBIA will be utilized effectively. Figure 10 shows the weed management phase in a plantation system using drone technology.

3.9. Irrigation Management. In recent years, crop irrigation information can be obtained through satellite remote sensing images from various platforms as it has an advantage in terms of crop coverage area. However, the problem of public coverage and satellite remote sensing that is not in the orbital position during the plant development stage affects drone technology's use completely [132]. Izzuddin et al. [133] proposed an installation of thermal infrared sensor on a drone to enable the system to obtain the canopy temperature as this sensor is lighter and can produce more stable information; however, it will easily influence by air temperature and human activity [134] compared to multispectral sensors.

Besides that, drones equipped with thermal cameras can detect possible pooling or leaks in any irrigation system. A single high-resolution integrated with geolocated map of the field will highlight stressed areas. This map can also be used in the context of variable rate irrigation (VRI) applications. VRI applications can optimize the irrigation system around the fields and automate the process based on data collected by sensors, maps, and GPS [135]. It can also contribute to identifying the water pollution around courses and bodies and consequent degradation of water-related ecosystems that might raise due to usage of agricultural chemicals that seep into nearby water system. Furthermore, drone application can also observe serious soil degradation, which threatens plant productivity [136].

4. Challenges of Drone Application/Limitations

The use of drone technology for the plantation sector is among the main challenges. The cost of procuring drones, sensors and related materials, flight time, limited payload, and frequently changing regulations by the relevant authorities increases the chances of utilizing the drone effectiveness. More comprehensive information on the opportunities and challenges of drone application for the plantation and environmental sectors were effectively discussed by Hardin and Jensen [137], Zhang and Kovacs [138], and Ken and Hugenholtz [139].

4.1. Regulations. Drones equipped with the right sensors can aid a farmer to navigate the location in the fields, observe it, and generate statistics data related to the health and status of the crops. Under the Department of Civil Aviation (DCA) regulations, all measurements and observations done using a drone must fall within the drone operator's visual line of sight (VLOS). The problem in drone application is most larger farms have larger VLOS distance. It is impossible to conduct multiple operations continuously and stitch the multiple images together into a larger map as this will take a lot of time and need technical expertise. Moreover, the use of UAVs for agriculture is more commercial-based, and all relevant legislation and national rules should be followed.

4.2. Operating Time. For legal and safety purposes, drones need to have an active pilot. Using a drone in agriculture does not facilitate multitasking. There must be someone to be present if something goes wrong. Even if a farmer is executing an autopilot flight, the pilot cannot walk away to take care of something else.

A common problem that usually arises is the estimation of the flight durations as it usually affects ideal conditions. A software may predict a time of flight based on a given area of interest, but in real conditions, it may take four or five times longer than the software prediction. Besides that, once the images are acquired, it need to be processed and analyzed to extract all the useful information. With an average supercomputer, few hours will be taken to analyze thousands of photos.

4.3. Disadvantages of the Use of UAVs. Though drone applications for precision agriculture are growing, there is a number of barriers to their successful widespread adoption. Various issues must be considered when employing a drone, and these includes the path-planning process that does not utilize an expert pilot, the high-speed ultra-low scenario, data downloading task in real-time application, size, and payload to prevent bottlenecks and software for automatic analysis [138]. Another deterrent to invest in drone applications is the high cost of purchasing an unmanned aerial system. On the other side, the lack of a consistent workflow encourages stakeholders to use ad hoc procedures for implementing precision applications. Furthermore, because precision agriculture necessitates data-intensive techniques for utilization of the collected images, qualified personnel and professionals are frequently required as a result, and an average farmer may require training or the assistance of an expert to assist with picture processing, thereby increasing the cost. Therefore, each farmer with a few and tiny agricultural lands may be unable to use drone technologies. Hence, stakeholders with vast cultivated areas who has higher profit rates can use more advanced and expensive drone management systems. The most industrial drones have a shorter flight duration, ranging from 20 min to 1 h, which can only cover restricted area at each flight. On the other hand, longer-flying drones are more costly. Furthermore, the successful utilization of drones is influenced by the weather. The flight should be postponed, for example, on a very bad day. The weight and size of the sensors in the low-cost drone are the drone's other restrictions such as smaller and medium-sized drones are usually less steady and precise, and less powerful engines and low-cost drones have difficulty reaching a specific altitude [140].

5. Conclusion and Recommendations

Precision agriculture has incorporated cutting-edge technologies to boost crop output over the last decade. These technologies are important in situations where it is impossible to spray chemicals on crops due to a lack of labor. This method also makes the work of spraying easier and faster. The suggested solution explains how to monitor crops using a multispectral camera mounted on a drone. The camera gathers photographs, and the geographic indicator analyzes them throughout a single trip. It may be easier to pinpoint the areas that require pesticide or fertilizer application based on the findings. The pesticides will be sprayed by the drone sprinkling system using GPS coordinates exclusively on affected regions where the NDVI has identified no vegetation. This could help cut down on resource waste like water and chemicals. Precision agriculture with drones is still in its early stages, and drone technology for agriculture applications has room for improvement. Enhanced image processing approach, less costly, minimum flight duration, new sensor designs, batteries, low volume sprayers, and nozzle types are all expected to be examined as drone technology advances. Drones based on remote sensing for agricultural applications should be the subject of a large number of experimental research. In the not-too-distant future, these systems will be more prominent in precision agriculture and environmental monitoring.

Abbreviations

BSR:	Basal stem rot
CCCI:	Canopy-chlorophyll content index
CNN:	Convolutional neural network
CWSI:	Crop-water stress index
DCA:	Department of Civil Aviation
DSM:	Digital surface model
GDSI:	Ganoderma disease severity index
GIS:	Geographic information system
GNSS:	Global navigation satellite system
GPS:	Global positioning system
GSM:	Global system for mobile communications
HSV:	Hue, saturation, value
ICT:	Information and communication technology
IMU:	Inertial measurement unit
IoT:	Internet of Things
IPM:	Integrated pest management
Lab:	A color-opponent space with dimension L for lightness and a and b for color-opponent dimensions
LCD:	Liquid-crystal display
LiDAR:	Light detection and ranging
LiPo:	Lithium-ion polymer
MAVLink:	A very lightweight messaging protocol for communicating with drones
MEMS:	Microelectromechanical system
MS:	Multispectral
NDVI:	Normalized difference vegetation index
NIR:	Near infrared reflectance
OBIA:	Object-based image analysis
PA:	Precision agriculture
RGB:	Red-green-blue
RPAS:	Remotely piloted aerial systems
RS:	Remote sensing
SSWM:	Site-specific weed management
TIR:	Thermal infrared
UAS:	Unmanned aerial systems
UAV:	Unmanned aerial vehicle
VIS-C:	Visible-color
VisualSFM:	Visual structure from motion system
VLOS:	Visual line of sight

VRI: Variable rate irrigation
YUV: One luminance and two chrominance.

Conflicts of Interest

The authors have declared that no conflict of interest exists.

Acknowledgments

The authors would like to thank Assoc. Prof. Dr. Nazmi Mat Nawi, Head of Laboratory, at Universiti Putra Malaysia, for the assistance, guidelines, and instruction.

References

[1] B. Kalantar, M. O. Idrees, S. Mansor, and A. A. Halins, "Smart counting – oil palm tree inventory with UAV," *Coordinates*, pp. 17–22, 2017.

[2] R. Corley and P. Tinker, *The Oil Palm*, vol. 592Wiley-Blackwell, 4 edition, 2008.

[3] W. Darmosarkoro and S. S. Edy, *Winarma Lahan dan Pemupukan Kelapa Sawit*, vol. 1, Pusat Penelitian Kelapa Sawit, 2003.

[4] D. W. Lamb and R. B. Brown, "PA–precision agriculture: remote-sensing and mapping of weeds in crops," *Journal of Agricultural Engineering Research*, vol. 78, no. 2, pp. 117–125, 2001.

[5] D. J. Mulla, "Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps," *Biosystems Engineering*, vol. 114, no. 4, pp. 358–371, 2013.

[6] S. K. Seelan, S. Laguette, G. M. Casady, and G. A. Seielstad, "Remote sensing applications for precision agriculture: a learning community approach," *Remote Sensing of Environment*, vol. 88, no. 1-2, pp. 157–169, 2003.

[7] J. V. Stanfford, "Implementing precision agriculture in the 21st century," *Journal of Agricultural Engineering Research*, vol. 76, no. 3, pp. 267–275, 2000.

[8] B. Kalantar, S. Mansor, M. I. Sameen, B. Pradhan, and H. Z. M. Shafri, "Drone-based land-cover mapping using a fuzzy unordered rule induction algorithm integrated into object-based image analysis," *International Journal of Remote Sensing*, vol. 38, no. 8-10, pp. 2535–2556, 2017.

[9] H. A. H. Al-najjar, B. Kalantar, B. Pradhan, and V. Saeidi, "Land cover classification from fused DSM and UAV images using convolutional neural networks," *Remote Sensing*, vol. 11, no. 12, p. 1461, 2019.

[10] B. K. G. Harandi, S. B. Mansor, and H. Z. M. Shafri, "Image mosaic methods for UAV sequence images," in *ACRS 2015 - 36th Asian Conf. Remote Sens. Foster. Resilient Growth Asia, Proc*, 2015.

[11] D. Krijnen and C. Dekker, "AR drone 2.0 with Subsumption architecture," in *In proceedings of the Artificial intelligence research seminar*, 2014.

[12] A. Cavoukian, *Privacy and drones: Unmanned Aerial Vehicles*, Information and Privacy Commissioner of Ontario, Canada, 2012.

[13] S. G. Gupta, D. M. Ghonge, and P. M. Jawandhiya, "Review of unmanned aircraft system (UAS)," *SSRN Electronic Journal*, vol. 2, 2013.

[14] B. Kalantar, S. B. Mansor, A. Abdul Halin, H. Z. M. Shafri, and M. Zand, "Multiple moving object detection from UAV videos using trajectories of matched regional adjacency graphs," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 9, pp. 5198–5213, 2017.

[15] H. Zhu, H. Nie, L. Zhang, X. Wei, and M. Zhang, "Design and assessment of octocopter drones with improved aerodynamic efficiency and performance," *Aerospace Science and Technology*, vol. 106, article 106206, 2020.

[16] S. Salazar-Cruz, F. Kendoul, R. Lozano, and I. Fantoni, "Real-time stabilization of a small three-rotor aircraft," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 44, no. 2, pp. 783–794, 2008.

[17] T. S. Kabra, A. V. Kardile, D. BMane, P. R. Bhosale, and A. M. Belekar, "Design, Development & optimization of a quadcopter for agricultural applications," *International Research Journal of Engineering and Technology*, vol. 4, no. 7, 2017.

[18] J. Verbeke, D. Hulens, H. Ramon, T. Goedeme, and J. De Schutter, "The design and construction of a high endurance hexacopter suited for narrow corridors," in *2014 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 543–551, 2014.

[19] G. W. Wasantha and S. Wang, "Heavy payload tethered hexaroters for agricultural applications: power supply design," *International Research Journal of Engineering and Technology*, vol. 2, pp. 641–645, 2015.

[20] B. Kalantar, N. Ueda, H. A. H. Al-Najjar, H. Moayedi, A. A. Halin, and S. Mansor, "Uav and lidar image registration: a surf-based approach for ground control points selection," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLII-2/W13, pp. 413–418, 2019.

[21] B. Kalantar, S. B. Mansor, H. Z. M. Shafri, and A. A. Halin, "Integration of template matching and object-based image analysis for semi-Automatic oil palm tree counting in UAV images," in *Proceedings of the 37th Asian Conference on Remote Sensing, ACRS 2016*, vol. 3, 2016.

[22] D. B. Kingston, R. Beard, T. McLain, M. Larsen, and W. Ren, "Autonomous vehicle technologies for small fixed-wing UAVs," *Journal of Aerospace Computing, Information, and Communication*, vol. 2, no. 1, pp. 92–108, 2005.

[23] A. Lindqvist, E. Fresk, and G. Nikolakopoulos, "Optimal design and modeling of a tilt wing aircraft," in *2015 23rd Mediterranean Conference on Control and Automation (MED)*, pp. 701–708, 2015.

[24] S. Bose, R. Verma, K. Garuda, A. Tripathi, and S. Clement, "Modeling, analysis and fabrication of a thrust vectoring spherical VTOL aerial vehicle," in *2014 IEEE aerospace conference*, 2014.

[25] C. W. Lum, K. Gauksheim, T. Kosel, and T. McGeer, "Assessing and estimating risk of operating unmanned aerial systems in populated areas," in *11th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, including the AIAA Balloon Systems Conference and 19th AIAA Lighter-Than*, 2011.

[26] Z. Mohammad Zain, D. S. Ganraj, and A. K. Hussin, "An ultralight helicopter for rice farmers," in *19th AIAA Applied Aerodynamics Conference*, 2001.

[27] M. Hejduk, "The use of unmanned aerial vehicles - drones supply courier," *Thesis Inzynierska*, International University of Logistics and Transport, Wroclaw, 2015.

[28] G. Yang, J. Liu, C. Zhao et al., "Unmanned aerial vehicle remote sensing for field-Based crop phenotyping: current

status and perspectives," *Frontiers in Plant Science*, vol. 8, p. 1111, 2017.

[29] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, "A Review on UAV-Based Applications for Precision Agriculture," *Information*, vol. 10, no. 11, p. 349, 2019.

[30] J. Xue and B. Su, "Significant remote sensing vegetation indices: a review of developments and applications," *Journal of sensors*, vol. 2017, Article ID 1353691, 17 pages, 2017.

[31] M. S. Tehrany, H. Özener, B. Kalantar et al., "Application of an ensemble statistical approach in spatial predictions of bushfire probability and risk mapping," *Journal of sensors*, vol. 2021, Article ID 6638241, 31 pages, 2021.

[32] M. Maimaitijiang, A. Ghulam, P. Sidike et al., *Unmanned Aerial System (UAS)-Based Phenotyping of Soybean Using Multi-Sensor Data Fusion and Extreme Learning Machine*, vol. 134, 2017.

[33] M. Hassanein, Z. Lari, and N. El-Sheimy, "A new vegetation segmentation approach for cropped fields based on threshold detection from hue histograms," *Sensors*, vol. 18, no. 4, p. 1253, 2018.

[34] L. Deng, Z. Mao, X. Li, Z. Hu, F. Duan, and Y. Yan, "UAV-based multispectral remote sensing for precision agriculture: a comparison between different cameras," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 146, pp. 124–136, 2018.

[35] S. Bhandari, A. Raheja, M. R. Chaichi et al., "Effectiveness of uav-based remote sensing techniques in determining lettuce nitrogen and water stresses," in *Proceedings of 14th International Conference on Precision Agriculture*, pp. 1066403–1066415, 2018.

[36] M. Hassanalian and A. Abdelkefi, "Classifications, applications, and design challenges of drones: a review," *Progress in Aerospace Science*, vol. 91, pp. 99–131, 2017.

[37] A. C. Watts, V. G. Ambrosia, and E. A. Hinkley, "Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use," *Remote Sensing*, vol. 4, no. 6, pp. 1671–1692, 2012.

[38] M. Arjomandi, *Classification of Unmanned Aerial Vehicles Related Papers*, 2007.

[39] *911 Security Newsletter October 2020 Newsletter*, The University of Adelaide, 2007.

[40] R. R. Shamshiri, I. A. Hameed, S. K. Balasundram, D. Ahmad, C. Weltzien, and M. Yamin, "Fundamental research on unmanned aerial vehicles to support precision agriculture in oil palm plantations," *Agricultural Robots-Fundamentals and Application*, J. Zhou and B. Zhang, Eds., pp. 91–116, 2018.

[41] P. Gennari, A. Heyman, and M. Kainu, *FAO statistical pocketbook*, World food and agriculture. Food Agric. Organ, United Nations, Rome, Italy, 2015.

[42] R. R. Shamshiri, "A breakthrough in oil palm precision agriculture: smart management of oil palm plantations with autonomous UAV imagery and robust machine vision," in *Int. Conf. Agric. Food Eng.*, 2016.

[43] M. B. A. Gibril, H. Z. M. Shafri, A. Shanableh, R. Al-Ruzouq, A. Wayayok, and S. J. Hashim, "Deep convolutional neural network for large-scale date palm tree mapping from uav-based images," *Remote Sensing*, vol. 13, no. 14, p. 2787, 2021.

[44] R. R. Shamshiri, *Integration of Smart Sensors and Robotics in Increasing Agricultural Productivity with Higher Yields at Lower Costs*, Asian Sp. Technol. Summit, 2017.

[45] P. Mylonas, Y. Voutos, and A. Sofou, "A Collaborative Pilot Platform for Data Annotation and Enrichment in Viticulture," *Information*, vol. 10, no. 4, p. 149, 2019.

[46] K. Chartzoulakis and M. Bertaki, "Sustainable water management in agriculture under climate change," *Agriculture and Agricultural Science Procedia*, vol. 4, pp. 88–98, 2015.

[47] P. Saccon, "Water for agriculture, irrigation management," *Applied Soil Ecology*, vol. 123, pp. 793–796, 2018.

[48] P. Garre and A. Harish, "Autonomous agricultural pesticide spraying UAV," in *IOP Conference Series: Materials Science and Engineering*, vol. 455, Bristol, UK, 2018.

[49] B. Allreda, L. Martinez, M. K. Fessehazion et al., "Overall results and key findings on the use of UAV visible-color, multispectral, and thermal infrared imagery to map agricultural drainage pipes," *Agricultural Water Management*, vol. 232, p. 106036, 2020.

[50] H. Lu, T. Iseley, J. Matthews, W. Liao, and M. Azimi, "An ensemble model based on relevance vector machine and multi-objective salp swarm algorithm for predicting burst pressure of corroded pipelines," *Journal of Petroleum Science and Engineering*, vol. 203, article 108585, 2021.

[51] M. P. Christiansen, M. S. Laursen, R. N. Jørgensen, S. Skovsen, and R. Gislum, "Designing and testing a uav mapping system for agricultural field surveying," *Sensors*, vol. 17, no. 12, p. 2703, 2017.

[52] J. Primicerio, S. Filippo, D. Gennaro et al., "A flexible unmanned aerial vehicle for precision agriculture," *Precision Agriculture*, vol. 13, no. 4, pp. 517–523, 2012.

[53] L. G. Santesteban, S. F. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. B. Royo, and A. Matese, "High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard," *Agricultural Water Management*, vol. 183, pp. 49–59, 2017.

[54] A. Vasudevan, D. A. Kumar, and N. S. Bhuvaneswari, "Precision farming using unmanned aerial and ground vehicles," in *2016 IEEE technological innovations in ICT for agriculture and rural development (TIAR)*, pp. 146–150, 2016.

[55] X. Li, Y. Zhao, J. Zhang, and Y. Dong, "A hybrid pso algorithm based flight path optimization for multiple agricultural uavs," in *2016 IEEE 28th international conference on tools with artificial intelligence (ICTAI)*, pp. 691–697, 2016.

[56] B. Dai, Y. He, F. Gu, L. Yang, J. Han, and W. Xu, "A vision-based autonomous aerial spray system for precision agriculture," in *2017 ieee international conference on robotics and biomimetics (ROBIO)*, pp. 507–513, 2017.

[57] K. Uto, H. Seki, G. Saito, and Y. Kosugi, "Characterization of rice paddies by a UAV-mounted miniature hyperspectral sensor system," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 6, no. 2, pp. 851–860, 2013.

[58] R. O. Bura, S. W. Apriyani, K. Ariwibawa, and E. Adharian, "UAV application for oil palm harvest prediction," *Journal of Physics Conference Series*, vol. 1130, p. 012001, 2018.

[59] T. Kattenborn, M. Sperlich, K. Bataua, and B. Koch, "Automatic single tree detection in plantations using UAV-based photogrammetric point clouds," *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 40, pp. 139–144, 2014.

[60] W. H. Maes and K. Steppe, "Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture," *Trends in Plant Science*, vol. 24, no. 2, pp. 152–164, 2019.

[61] B. P. Hudzietz and S. Saripalli, "An experimental evaluation of 3D terrain mapping with an autonomous helicopter," *International Society for Photogrammetry and Remote Sensing*, vol. 38, 2011.

[62] H. Freimuth and M. König, "Generation of waypoints for uav-assisted progress monitoring and acceptance of construction work," in *15th International Conference on Construction Applications of Virtual Reality*, 2015.

[63] S. Siebert and J. Teizer, "Mobile 3D mapping for surveying earthwork projects using an unmanned aerial vehicle (UAV) system," *Automation in Construction*, vol. 41, pp. 1–14, 2014.

[64] Z. Yang, "Fast template matching based on normalized cross correlation with centroid bounding," in *2010 International Conference on Measuring Technology and Mechatronics Automation*no. 2, pp. 224–227, 2010.

[65] *SOPB Sarawak Oil Palms Berhad Annual Report 2018*, Sarawak Oil Palms Berhad, 2018.

[66] A. J. Pinz, "A computer vision system for the recognition of trees in aerial photographs," *Multisource Data Integration in Remote Sensing*, vol. 3099, pp. 111–124, 1991.

[67] R. Woodham and R. Pollock, "The automatic recognition of individual trees in aerial images of forests based on a synthetic tree crown image model," *Doctoral dissertation*, University of British Columbia, 1996.

[68] M. A. Mansur, R. B. Mukhtar, and J. Al-Doksi, "The usefulness of unmanned airborne vehicle (UAV) imagery for automated palm oil tree counting," *Research Journal*, vol. 1, 2014.

[69] L. Wang, P. Gong, and G. S. Biging, "Individual tree-crown delineation and treetop detection in high-spatial-resolution aerial imagery," *Photogrammetric Engineering and Remote Sensing*, vol. 70, no. 3, pp. 351–357, 2004.

[70] T. Brandtberg and F. Walter, "Automated delineation of individual tree crowns in high spatial resolution aerial images by multiple-scale analysis," *Machine Vision and Applications*, vol. 11, no. 2, pp. 64–73, 1998.

[71] A. Tellaeche, X. P. BurgosArtizzu, G. Pajares, A. Ribeiro, and C. Fernández-Quintanilla, "A new vision-based approach to differential spraying in precision agriculture," *Computers and Electronics in Agriculture*, vol. 60, no. 2, pp. 144–155, 2008.

[72] G. Sylvester, *E-Agriculture in action: drones for agriculture*, Food and Agriculture Organization ofn the United Nations and International Telecommunication Union, Bangkok, 2018.

[73] D. Zhang, L. Chen, R. Zhang et al., "Evaluating effective swath width and droplet distribution of aerial spraying systems on M-18B and thrush 510G airplanes," *International Journal of Agricultural and Biological Engineering*, vol. 8, pp. 21–30, 2015.

[74] S. R. Kurkute, B. D. Deore, P. Kasar, M. Bhamare, and M. Sahane, "Drones for smart agriculture: a technical report," *International Journal for Research in Applied Science and Engineering Technology*, vol. 6, no. 4, pp. 341–346, 2018.

[75] B. Sadhana, G. Naik, R. J. Mythri, P. G. Hedge, and K. S. B. Shyama, "Development of quad copter based pesticide spraying mechanism for agricultural applications," *International Journal of Innovative Research in Electrical, Electronics*, vol. 5, no. 2, pp. 121–123, 2017.

[76] K. Gayathri Devi, N. Sowmiya, K. Yasoda, K. Muthulakshmi, and B. Kishore, "Review on application of drones for crop health monitoring and spraying pesticides and fertilizer," *Journal of Critical Reviews*, vol. 7, no. 6, pp. 667–672, 2020.

[77] S. Kedari, P. Lohagaonkar, M. Nimbokar, G. Palve, and P. Yevale, "Quadcopter-a smarter way of pesticide spraying," *Imperial Journal of Interdisciplinary Research*, vol. 2, no. 6, 2016.

[78] R. Laudien, G. Bareth, and R. Doluschitz, "multitemporal hyperspectral data analysis for regional detection of plant stress by using an airborne- and tractor-based spectrometer – case study: sugar beet disease Rhizoctonia Solani –," in *Proceedings of the Analysis and Applications, International Society for Photogrammetry and Remote Sensing (ISPRS)*, Beijing, China, 2005.

[79] I. Colomina and P. Molina, "Unmanned aerial systems for photogrammetry and remote sensing: a review," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 92, pp. 79–97, 2014.

[80] F. Nex and F. Remondino, "UAV for 3D mapping applications: a review," *Applied Geomatics*, vol. 6, no. 1, pp. 1–15, 2014.

[81] J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, and G. Bareth, "Estimating Biomass of Barley Using Crop Surface Models (CSMs) Derived from UAV-Based RGB Imaging," *Remote Sensing*, vol. 6, no. 11, pp. 10395–10412, 2014.

[82] F. A. Vega, F. C. Ramírez, M. P. Saiz, and F. O. Rosúa, "Multitemporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop," *Biosystems Engineering*, vol. 132, pp. 19–27, 2015.

[83] R. A. Díaz-Varela, R. D. Rosala, L. León, and P. J. Zarco-Tejada, "High-resolution airborne uav imagery to assess olive tree crown parameters using 3d photo reconstruction: application in breeding trials," *Remote Sensing*, vol. 7, no. 4, pp. 4213–4232, 2015.

[84] J. Torres-Sánchez, F. López-Granados, N. Serrano, O. Arquero, and J. M. Peña, "High-throughput 3-D monitoring of agricultural-tree plantations with unmanned aerial vehicle (UAV) technology," *Technology*, vol. 10, no. 6, 2015.

[85] L. Kumar, K. S. Schmidt, S. Dury, and A. K. Skidmore, "Imaging spectrometry and vegetation science," in *Imaging Spectrometry - Basic Principles and Prospective Application*, F. D. Meer and S. M. Jong, Eds., vol. 4, pp. 111–155, Remote Sensing and Digital Image Processing, 2001.

[86] W. Koppe, M. L. Gnyp, S. D. Hennig et al., "Multi-temporal hyperspectral and radar remote sensing for estimating winter wheat biomass in the North China Plain," *Photogrammetrie-Fernerkundung-Geoinformation*, vol. 2012, no. 3, pp. 281–298, 2012.

[87] S. Migdall, H. Bach, J. Bobert, M. Wehrhan, and W. Mauser, "Inversion of a canopy reflectance model using hyperspectral imagery for monitoring wheat growth and estimating yield," *Precision Agriculture*, vol. 10, no. 6, pp. 508–524, 2009.

[88] C. Yang, J. H. Everitt, and J. M. Bradford, "Yield estimation from hyperspectral imagery using spectral angle mapper (SAM)," *Transactions of the ASABE*, vol. 51, no. 2, pp. 729–737, 2008.

[89] V. Hoyos-Villegas and F. B. Fritschi, "Relationships among vegetation indices derived from aerial photographs and soybean growth and yield," *Crop Science*, vol. 53, no. 6, pp. 2631–2642, 2013.

[90] T. Sakamoto, A. A. Gitelson, A. L. Nguy-Robertson et al., "An alternative method using digital cameras for continuous

monitoring of crop status," *Agricultural and Forest Meteorology*, vol. 154-155, pp. 113–126, 2012.

[91] P. J. Zarco-Tejada, J. A. Berni, L. Suárez, and E. Fereres, "A new era in remote sensing of crops with unmanned robots," *Proceedings of SPIE*, vol. 10, p. 7480, 2008.

[92] T. Chu, R. Chen, J. A. Landivar, M. M. Maeda, C. Yang, and M. J. Starek, "Cotton growth modeling and assessment using unmanned aircraft system visual-band imagery," *Journal of Applied Remote Sensing*, vol. 10, no. 3, article 036018, 2016.

[93] A. Gracia-Romero, S. C. Kefauver, O. Vergara-Díaz et al., "Comparative performance of ground vs. aerially assessed RGB and multispectral indices for early-growth evaluation of maize performance under phosphorus fertilization," *Frontiers in Plant Science*, vol. 8, p. 2004, 2017.

[94] A. C. Kyratzis, D. P. Skarlatos, G. C. Menexes, V. F. Vamvakousis, and A. Katsiotis, "Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed Mediterranean environment," *Frontiers in Plant Science*, vol. 8, p. 1114, 2017.

[95] X. Zhou, H. B. Zheng, X. Q. Xu et al., "Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 130, pp. 246–255, 2017.

[96] J. Bendig, A. Bolten, and G. Bareth, "Introducing a low-COST mini-UAV for thermal- and multispectral-imaging," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 39, pp. 345–349, 2012.

[97] M. Reinecke and T. Prinsloo, "The influence of drone monitoring on crop health and harvest size," in *2017 1st International conference on next generation computing applications (NextComp)*, pp. 5–10, 2017.

[98] A. K. Bhandari, A. Kumar, and G. K. Singh, "Feature extraction using normalized difference vegetation index (NDVI): a case study of Jabalpur City," *Procedia Technology*, vol. 6, pp. 612–621, 2012.

[99] J. W. Rouse, R. H. Haas, J. A. Schell, and D. W. Deering, "Monitoring vegetation systems in the great plains with ERTS," in *3rd ERTS Symp. NASA SP-351*, pp. 309–317, Washingt. DC, 1973.

[100] DJI DJI - Official Website, https://www.dji.com.

[101] J. Huang, H. Wang, Q. Dai, and D. Han, "Analysis of NDVI data for crop identification and yield estimation," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 11, pp. 4374–4384, 2014.

[102] A. Matese, P. Toscano, S. F. GennaroDi et al., "Intercomparison of uav, aircraft and satellite remote sensing platforms for precision viticulture," *Remote Sensing*, vol. 7, no. 3, pp. 2971–2990, 2015.

[103] R. Austin, "Unmanned aircraft systems: UAVS design," in *Development and Deployment*, John Wiley & Sons, 54th edition, 2010.

[104] T. Duan, S. C. Chapman, Y. Guo, and B. Zheng, "Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle," *Field Crops Research*, vol. 210, pp. 71–80, 2017.

[105] M. Kerkech, A. Hafiane, and R. Canals, "Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images," *Computers and Electronics in Agriculture*, vol. 155, pp. 237–243, 2018.

[106] S. Liaghat, R. Ehsani, S. Mansor et al., "Early detection of basal stem rot disease (Ganoderma) in oil palms based on hyperspectral reflectance data using pattern recognition algorithms," *International Journal of Remote Sensing*, vol. 35, no. 10, pp. 3427–3439, 2014.

[107] G. Singh, "Ganoderma - the scourge of oil palm in the coastal area," in *Proceedings of Ganoderma workshop, Bangi, Selangor, Malaysia, 11 September 1990*, pp. 7–35, 1991.

[108] H. Z. M. Shafri and N. Hamdan, "Hyperspectral imagery for mapping disease infection in oil palm plantation using vegetation indices and red edge techniques," *American Journal of Applied Sciences*, vol. 6, no. 6, pp. 1031–1035, 2009.

[109] I. Manfredonia, C. Stallo, M. Ruggieri, G. Massari, and S. Barbante, "An early-warning aerospace system for relevant water bodies monitoring," in *2015 IEEE Metrology for Aerospace (MetroAeroSpace)*, pp. 536–540, 2015.

[110] J. Gago, C. Douthe, R. E. Coopman et al., "UAVs challenge to assess water stress for sustainable agriculture," *Agricultural Water Management*, vol. 153, pp. 9–19, 2015.

[111] M. A. Izzuddin, A. Hamzah, M. N. Nisfariza, and A. S. Idris, "Analysis of multispectral imagery from unmanned aerial vehicle (UAV) using object-based image analysis for detection of ganoderma disease in oil palm," *Journal of Oil Palm Research*, vol. 32, pp. 497–508, 2020.

[112] K. Anderson and K. J. Gaston, "Lightweight unmanned aerial vehicles will revolutionize spatial ecology," *Frontiers in Ecology and the Environment*, vol. 11, no. 3, pp. 138–146, 2013.

[113] E.-C. Oerke, "Crop losses to pests," *The Journal of Agricultural Science*, vol. 144, no. 1, pp. 31–43, 2006.

[114] C. R. Thompson, J. A. Dille, and D. E. Peterson, "Weed competition and management in Sorghum," *Sorghum: A State of the Art and Future Perspetives*, vol. 58, pp. 347–360, 2019.

[115] A. C. Guglielmini, A. M. C. Verdú, and E. H. Satorre, "Competitive ability of five common weed species in competition with soybean," *International journal of pest management*, vol. 63, no. 1, pp. 30–36, 2017.

[116] S. Korav, V. Ram, L. I. P. Ray, R. Krishnappa, N. J. Singh, and N. Premaradhya, "Weed pressure on growth and yield of groundnut (Arachis hypogaea L.) in Meghalaya, India," *International Journal of Current Microbiology and Applied Sciences*, vol. 7, pp. 2852–2858, 2018.

[117] H. Kaur, G. Singh Brar, and P. P. A. Shete, "A Review on different Weed Management approaches," *International Journal of Current Microbiology and Applied Sciences*, vol. 8, no. 8, pp. 2854–2859, 2019.

[118] A. Zohaib, T. Abbas, and T. Tabassum, "Weeds cause losses in field crops through allelopathy," *Notulae Scientia Biologicae*, vol. 8, no. 1, pp. 47–56, 2016.

[119] M. Hassanein and N. El-Sheimy, "An efficient weed detection procedure using low-cost UAV imagery system for precision agriculture applications," *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, vol. XLII-1, pp. 181–187, 2018.

[120] K. R. Krishna, *Agricultural Drones: A Peaceful Pursuit*, Apple Academic Press, Inc., 2018.

[121] M. Crimaldi, V. Cristiano, A. VivoDe, M. Isernia, P. Ivanov, and F. Sarghini, "Neural network algorithms for real time plant diseases detection using UAVs," *Lecture Notes in Civil Engineering*, vol. 67, pp. 827–835, 2020.

[122] F. López-Granados, "Weed detection for site-specific weed management: mapping and real-time approaches," *Weed Research*, vol. 51, no. 1, pp. 1–11, 2011.

[123] T. K. Alexandridis, A. A. Tamouridou, X. E. Pantazi et al., "Novelty detection classifiers in weed mapping: Silybum marianum detection on UAV multispectral images," *Sensors*, vol. 17, no. 9, p. 2007, 2017.

[124] A. A. Tamouridou, T. K. Alexandridis, X. E. Pantazi et al., "Application of multilayer perceptron with automatic relevance determination on weed mapping using uav multispectral imagery," *Sensors*, vol. 17, no. 10, p. 2307, 2017.

[125] F. Castaldi, F. Pelosi, S. Pascucci, and R. Casa, "Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize," *Precision Agriculture*, vol. 18, 2017.

[126] J. P. T. Lambert, H. L. Hicks, D. Z. Childs, and R. P. Freckleton, "Evaluating the potential of unmanned aerial systems for mapping weeds at field scales: a case study with Alopecurus myosuroides," *Weed Research*, vol. 58, no. 1, pp. 35–45, 2018.

[127] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review," *Computers and Electronics in Agriculture*, vol. 151, pp. 61–69, 2018.

[128] A. I. de Castro, J. Torres-Sánchez, J. M. Peña, F. M. Jiménez-Brenes, O. Csillik, and F. López-Granados, "An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery," *Remote Sensing*, vol. 10, no. 3, p. 285, 2018.

[129] M. Pérez-Ortiz, J. M. Peña, P. Antonio Gutiérrez, J. Torres-Sánchez, C. Hervás-Martínez, and F. López-Granados, "Selecting patterns and features for between- and within-crop-row weed mapping using UAV-imagery," *Expert Systems with Applications*, vol. 47, pp. 85–94, 2016.

[130] J. Gao, W. Liao, D. Nuyttens et al., "Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery," *International Journal of Applied Earth Observation and Geoinformation*, vol. 67, pp. 43–53, 2018.

[131] M. Esposito, M. Crimaldi, V. Cirillo, F. Sarghini, and A. Maggio, "Drone and sensor technology for sustainable weed management: a review," *Chemical and Biological Technologies in Agriculture*, vol. 8, 2021.

[132] W. Ren, D. Wu, and L. Qin, "Preliminary study on data collecting and processing of unmanned airship low altitude hyperspectral remote sensing," *Ecology and Environmental Monitoring of Three Gorges*, vol. 1, pp. 52–57, 2016.

[133] Z. ZhiTao, B. Jiang, H. WenTing, F. QiuPing, C. ShuoBo, and C. Ting, "Cotton moisture stress diagnosis based on canopy temperature characteristics calculated from UAV thermal infrared image," *Transactions of the Chinese Society of Agricultural Engineering*, vol. 34, pp. 77–84, 2018.

[134] K. Ribeiro-Gomes, D. Hernández-López, J. F. Ortega, R. Ballesteros, T. Poblete, and M. A. Moreno, "Uncooled thermal camera calibration and optimization of the photogrammetry process for uav applications in agriculture," *Sensors*, vol. 17, no. 10, p. 2173, 2017.

[135] L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, and G. Egea, "Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet," *Biosystems Engineering*, vol. 165, pp. 77–87, 2018.

[136] J. Salmelin, I. Pölönen, H.-H. Puupponen et al., "Hyperspectral imaging of macroinvertebrates—a pilot study for detecting metal contamination in aquatic ecosystems," *Water, Air, & Soil Pollution*, vol. 229, no. 9, 2018.

[137] P. J. Hardin and R. R. Jensen, "Small-scale unmanned aerial vehicles in environmental remote sensing: challenges and opportunities," *GIScience & Remote Sensing*, vol. 48, no. 1, pp. 99–111, 2011.

[138] C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: a review," *Precision Agriculture*, vol. 13, no. 6, pp. 693–712, 2012.

[139] W. Ken and H. Hugenholtz Chris, "Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: a review of progress and challenges1," vol. 2, pp. 69–85,, 2014.

[140] J. Romeo, G. Pajares, M. Montalvo, J. M. Guerrero, M. Guijarro, and A. Ribeiro, "Crop row detection in maize fields inspired on the human visual perception," *Scientific World Journal*, vol. 2012, article 484390, 10 pages, 2012.