



Unmanned Aerial Vehicles (UAV) in Precision Agriculture: Applications and Challenges

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Abstract: Agriculture is the primary source of income in developing countries like India. Agriculture accounts for 17 percent of India's total GDP, with almost 60 percent of the people directly or indirectly employed. While researchers and planters focus on a variety of elements to boost productivity, crop loss due to disease is one of the most serious issues they confront. Crop growth monitoring and early detection of pest infestations are still a problem. With the expansion of cultivation to wider fields, manual intervention to monitor and diagnose insect and pest infestations is becoming increasingly difficult. Failure to apply on time fertilizers and pesticides results in more crop loss and so lower output. Farmers are putting in greater effort to conserve crops, but they are failing most of the time because they are unable to adequately monitor the crops when they are infected by pests and insects. Pest infestation is also difficult to predict because it is not evenly distributed. In the recent past, modern equipment, tools, and approaches have been used to replace manual involvement. Unmanned aerial vehicles serve a critical role in crop disease surveillance and early detection in this setting. This research attempts to give a review of the most successful techniques to have precision-based crop monitoring and pest management in agriculture fields utilizing unmanned aerial vehicles (UAVs) or unmanned aircraft. The researchers' reports on the various types of UAVs and their applications to early detection of agricultural diseases are rigorously assessed and compared. This paper also discusses the deployment of aerial, satellite, and other remote sensing technologies for disease detection, as well as their Quality of Service (QoS).

Keywords: UAV; crop monitoring; pest management; remote sensing

1. Introduction

Most of the developed countries have adopted the latest technologies such as Photogrammetry and Remote Sensing (RS) [1,2] for precision agriculture [3,4] using Unmanned Aerial Vehicles (UAV) to make a good agriculture farm with minor infection. It will help the farmers with more crop productivity, quality, and, most importantly, the farmers' lesser workload. Further it can be used for spraying fertilizer and pesticides. Usually, the UAV's are developed with an automated drone system with sensors and cameras in order to monitor the condition and height of the crops. There are various types of UAV models have been developed. Based on the agriculture farm, select proper and appropriate UAVs should. The role of UAV in precision management is taken care by the captured spectral images. The multispectral camera will monitor the condition of the crop by scanning the entire crop field. The actuated drones mounted with cameras will identify the pest and insect hot spots. The UAVs and remote-sensing techniques mentioned above help the farmers to



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). take appropriate measures at the right time to protect the crops from diseases. The UAV with low-altitude remote sensing has more advantages like good mobility, easy construction, and high resolution for obtaining the images [5]. The quality of the crop and yield benefits depends on biotic and abiotic factors. In the past, the farmers rely based on their experiences for the production of the crops. Different types of farmers are moving towards remote sensing platforms like UAV-based technology, which helps them protect the crops. In the future, precision agriculture will rely on Sensors, Robotics, the Internet of Things, Machine Learning, and Decision-based support systems. In [6], IoT-based technology has also been adapted to agricultural systems, incorporating cloud computing, big data storage, security issues, and analytics. In [7], they implemented an energy harvesting mechanism using solar energy and a wind turbine by integrating a long-range (LoRa) communication modem in agricultural field.

This review contributes the best solutions for protecting the crop and pest management to solve the farmer's problem and their day-to-day challenges in the agriculture field. We provide a brief overview to the necessity for UAVs. The goal of precision farming using remote sensing technologies is explained to reduce the potential risks and improve the agricultural yield. We focus on UAVs and their types with clear explanations with a comparison between the different types of UAVs including their technical specifications. The role of UAV in precision pest management is discussed. We provide the conclusion with a challenges and future scope in precision agriculture.

The rest of the paper is organized as follows. Section 2 gives a brief overview about the precision agriculture. Section 3 describes different types of UAVs. Section 4 juxtaposed the qualitative parameters of various types of UAVs and their applications in precision agriculture. Section 5 investigates the role of UAVs in precision pest management. In the last section we have drawn our conclusions.

2. Precision Agriculture

Precision agriculture (PA) helps farmers make crucial decisions at the right time by analyzing a vast amount of data regarding the environment and crop details. Thus, PA helps the farmers marching towards more production with quality to meet the required demand. Remote Sensing (RS) plays a vital role in crop evaluation and soil health conditions. It indicates the problems at the right time and helps to resolve the problem wisely. Figure 1 describes various remote sensing platforms used for precision agriculture.



Figure 1. RS Platforms in precision agriculture.

UAV is flexible for most applications and addresses the solutions for the problems faced by other RS platforms [8].

It can be easily accessible and provides accurate data. Further, it is cost-effective and easy to deploy anywhere and can operate real-time spatial images compared with other

traditional RS Platforms. Table 1 presented a detailed comparison of the quality of services provided by the various types of RS Platforms in Precision Agriculture.

Quality of Sorvices	Types of RS Platforms				
Quality of Services	UAV	Satellite	Manned Aircraft	Ground Based	
Flexibility	high	low	low	low	
Adaptability	high	low	low	low	
Cost	low	high	high	low	
Time Consumption	low	low	low	high	
Risk	low	average	high	low	
Accuracy	high	low	high	moderate	
Deployment	easy	difficult	complex	moderate	
Feasibility	yes	no	no	yes	
Availability	yes	no	yes	no	
Operability	easy	complex	complex	easy	

Table 1. QOS comparison of RS platforms used in precision agriculture.

3. Types of Unmanned Aerial Vehicle (UAV)

UAVs describe vehicles with weights around or lower to 25 kg which do not need a human to fly them as they can be managed remotely. A quick survey can be easily achieved over a wide range of area through unmanned aerial vehicles [9]. UAVs can be applied for analyzing images, ground monitoring, and in-depth situation analysis of a crop [8]. We can categorize UAVs into various types based on the number of rotors, speed, application, mechanism, etc. UAVs with weights greater than or equal to 25 kg have specific rules and laws to fly. As a result, weight can be a significant factor for distinguishing between the UAVs while the vehicle takes off. Firstly, we can see very heavy UAVs which weigh around 2 tons or more. They will be able to carry enough fuel and are mainly used for military purposes. Secondly, some UAVs weigh 200–2000 kgs and 50–200 kgs. These are used for various applications extensively and can hold enough fuel to travel for longer. Finally, we have lightweight UAVs weighing around 5 to 50 kgs that finds uses in agriculture purposes.

Further, we have micro-UAVs which weigh less than 5 kgs. UAVs that are lighter than 5 kg are easy for take-off and less expensive than heavier vehicles. It can be fixed-wing, Single Rotor, Multi Rotor Landing (VTOL) UAVs, and Hybrid Vertical Take-off. There is a vast difference in the structure of fixed-wing and multi-rotor. Their time of flying, endurance, and type of energy differ entirely from each other. A single motor is slightly different from multi-rotors. The single rotor contains two rotors in which one more oversized rotor is on the top, and the other is small and fixed on the tail. Multi-rotor can be Tricopter, Quadcopter, Hexacopter, and Octocopter based on the number of rotors and applications [10]. We discuss the various types of UAVs depicts in Figure 2 and Table 2.



Figure 2. Types of UAV.

Deversetors	Types of UAV				
rarameters	Fixed Wing	Single Rotor	Multi-Rotor	Hybrid VTOL	
No. of Rotors	1	1(1 Big Sized and Small Sized on the tail of the drone)	Tricopter-3 Quadcopter-4 Hexacopter-6 Octocopter-8	1	
Manufacture and Maintenance	Simple	Complex	Complex	Complex	
Cost	High	High	Low	High	
Average Flying Time	2 h (Battery) 16 h (Powered by Gas Engine)	Higher (Powered by Gas Engine)	Limited (20–30 min)	Ability to cover longer distances	
Endurance	More	More (with Gas Power)	Limited	More	
Energy	Battery—They never utilize energy to stay afloat on air, Gas Engine	Gas Power	Battery—They utilize energy to stay afloat on air	Battery	
Speed	Fast Flying Speed	Limited	Limited	Fast Flying Speed	
Applications	Long-Distance Aerial Mapping and Surveillance	Aerial Scanning	Aerial Photography, Short Distance Aerial Mapping and Surveillance	Mapping and Land Surveying, Mining, Surveillance and Security	
Drawbacks	Aerial photography is not applicable because it needs to be motionless in the air for a period.	Harder to fly, Dangerous to handle	Limited Payload	Imperfect in hovering Limited Payload	
Training Required in Flying	Required (runway or a Catapult Launcher- to set a fixed-wing in air, Parachute or a Net- Landing)	Not Required	Not Required	Not Required	

Table 2. Comparison of Types of UAV.

3.1. Fixed Winged

As can be seen in Figure 3, A fixed-winged UAV does data collection through remote operation mode. Fabrication of a simple fixed-wing UAV is by a wingspan of 195 cm and a carbon-fiber body with one propeller engine. As a result, excellent aerodynamics can be provided with the added benefit of more flight time when speed increases in the places surveyed. Usually, such UAVs are equipped with high-resolution cameras for better mapping and surveillance from height. In addition, it has a straightforward flight system. Moreover, the architecture and maintenance of such UAVs are also relatively easy [11].



Figure 3. Fixed Wing.

3.2. Single Rotor

A single-rotor system consists of two different components: As can be seen in Figure 4, the helicopter and another system that controls the helicopter from ground level. The helicopter contains various parts connected to it, namely a flight controller, gyroscope, GPS receiver, transmitter for image and telemetry, the sensor for heading and spraying components. Similarly, the ground-level controlling system contains a telemetry receiver and a transmitter in a remote control. Moreover, in specific systems, forced-air engine cooling is installed to cool the engine when it reaches high altitude and when the flight speed is low. In order to sense the heeling and pitch angle of the aircraft and detect 3D positional velocity, vertical gyroscopes which have high precision are used. Another sensor using magnetic heading is used to make minor corrections of mistakes due to the changing fight directions. The elevation and location of the UAV can be detected using a pressure altimeter connected to it. Various control variables can be computed using Kalman filter and Proportional Integral Derivative (PID) algorithms [12].



Figure 4. Single rotor.

3.3. Hybrid Vertical Take-Off and Landing (VTOL)

Hybrid VTOL UAVs are Vehicles that have the benefit of both fixed-winged systems and multi-rotor systems. As shown in Figure 5, They are very efficient in take-off, which is similar to multi-rotor systems. At the same time, they fly with an efficiency of a fixed-wing system. Due to its combined features, the development and maintenance of hybrid systems are complex, as are their control systems. In this case, three controllers, namely horizontal, vertical, and transition, are used [8].



Figure 5. Hybrid VTOL.

3.4. Multi Rotor

Based on the number of rotors and their configuration, multi-Rotor can be classified. Some of the most frequently used multi-copters are tricopter, quadcopter, hexocopter, and octocopter.

3.4.1. Tri Copter

As can be seen in Figure 6, The general structure of tricopter has three rotors which will help balance the weight of the tricopter when it is flying. The movement of the rotors is in such a way that the right rotor will be in the clockwise direction. The other two rotors will move in the opposite direction. A servo method is used to negate the unbalanced clockwise torque, which is done by tilting the rotor present in the tail. As a result, a productive pitch has been developed using the three rotors in various directions to move forward. Thus, differentiating the left and right rotor thrust, rolling can be achieved. Similarly, the vehicles can be moved sideways also [13].



Figure 6. Tricopter.

3.4.2. Quad Copter

Quadcopter has a superior design of UAVs, and they have four rotors. These rotors generate the lift of this model. As shown in Figure 7, Out of these four rotors, two oppositely placed rotors rotate in a clockwise direction (CW), and the remaining two rotors rotate in a counter-lockwise direction (CCW). The movement of this model around the axis includes forward/backward movements called 'pitch,' moving laterally in left or right directions called 'roll' and clockwise and counterclockwise movements called 'yaw.' The Plus and cross configuration models (based on their shapes) of Quadcopter are. The cross model is more popular than the conventional one because of its increased stability over the plus model [14].

3.4.3. Hex Copter

The Greek word Hexa means six. Hexacopter is a drone that has six arms, and each of them is attached to a single high-speed BLDC motor. As can be seen in Figure 8, The airframe is made of glass fiber. Aluminum tubes ($500 \times 25 \text{ mm}$) are fixed to an arm mount in the outer edge of the airframe. The six motors are mounted at the far end of these tubes (see Plate 1). The airframe plate is the support structure over which the other parts of the drone, such as batteries, motor, support a flight-controlled GPS antenna and tube of high-speed capacity. It also hasFPV cameras, ESC, circuit boards, and sensors. This model is used to spray pesticides for various agricultural purposes with a maximum of 5-L capacity fluid tank attached to the bottom of the airframe, where the outlet of this tank is attached to the inlet of the spray motor. The outlet of the spray motor is connected to spray nozzles. A U-shaped bent aluminum pipe of $14 \times 1.5 \text{ mm}$ proportion is used to mount the parts like

a fluid tank, spray motor, and spray lance. The spray lance has four nozzles spaced in a gap of 45 cm, each spanning 1.3 m. The bottom area of the drone has landing gears below the spray unit so that take-off and landing of the model would be safe during and after the spray [15].



Figure 7. Quad copter.



Figure 8. Hexacopter.

3.4.4. Octocopter

Octocopter has eight rotors and is used as similar to Hexa UAV for agricultural spraying purposes. As can be seen in Figure 9, This has a diagonal wheelbase of 1630 mm diameter and can fly for 15 min with a 10 kg payload. It has six nozzles with 5–8 m spray width. This model was observed using the Time-resolved particle image velocimetry (TR-PIV) method to measure the movement of the sprayed droplets and their deposition. This observation method showed that two variables, such as rotor speed and position of the spray nozzle, influence the movement of deposition of the spray [16].



Figure 9. Octo copter.

4. Role of UAV in Precision Pest Management

Precision pest management can be used for monitoring the crops which identify the pest-affected places using remote sensing technologies, and control mechanisms such as pesticide spraying will be acted accordingly from prevention of diseases. For achieving this, both the technologies should be mounted on the UAV.

The Unmanned aerial vehicle can also be used for spraying fertilizer and pesticides on agricultural fields [9]. The UAV has a significant feature with good speed and accuracy in spraying system of the fertilizer and pesticides. The main parts of UAV used for spraying are:

- Pressure nozzle;
- Spraying controller;
- Pesticide box;
- Hall-flow sensor;
- Small diaphragm pump;
- Field-map interpretation system.

A sprayer is connected with UAV for spraying pesticides or fertilizers. It can be sprayed through the nozzle into droplets under pressure. The suitable pressure is produced to spray the fluid with the help of the spray motor. The spraying controller uses the Hall-flow sensor for estimating the fluid flow inside the system and initiates the nozzle of the sprayer. UAVs used for spraying purpose can be varied with their Speed, Payload, and number of nozzles used for spraying. UAV-based fertilizer and pesticide spraying methodology has more efficiency than the traditional systems. It reduces the human contact with hazardous gases. A limited amount of human power is required. The UAV reduces the time and expenses.

A detailed study is made on pest detection using Remote Sensing technology. Tables 3–6 show the pest detection in various types of crops, and the observations are analyzed through the captured spectral images by the UAV, Manned Aircraft, Satellite, and ground-based technology. Further in the Table 3, technical specification of the UAV is mentioned while capturing the images of the crops in different agricultural fields and locations.

ReferencesCrop NameType of UAVCameraNo. of Ref. 3Pest NameObservationsSourav Kumar Biola et al., 2021RiceMulti-RotorMulti-Spectral6Leaf NopperVisual Imspection of imagesWill Bight et al., 2021 161PineMulti-RotorMulti-BotorMulti-BotorBight et al., sylophilasVisual Imspection of imagesBergion, Farin Severine et al. 2021MaizeMulti-RotorMulti-BotorPhytesphethora GurmosisVisual Imspection of imagesAll, G et al. 2021RiceMulti-RotorHyperspectral4Phytophthora GurmosisVisual Imspection of imagesAll, G et al., 2021RiceMulti-RotorHyperspectral4Ustilaginoidea virensDamage assessmentsNayor, C et al., 2021 [23]GrapevineMulti-RotorHyperspectral4Fusarium head blightVisual Imspection of imagesMo, H et al., 2021WheatMulti-RotorHyperspectral6BursaphelenchussylophilusDamage assessmentsXiao, Y et al., 2021WheatMulti-RotorHyperspectral6Suraper estarium graminaemum (Gibberellazee)Visual ImagesGuo, A et al., 2021WheatMulti-RotorHyperspectral6SuraphelenchussylophilusDiscase MontoringCastigrando, A et al., 2021 [25]OliveMulti-RotorHyperspectral6SuraphelenchussylophilusVisual ImagesSurape Samery Kinger, SameryMulti-RotorHyperspectral6Cereoproterstrum grammorer			Parameters				
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Anton Louise P. de Ocampo and Elmer P. Dadios 2021 [34]SolanummelongenaMulti-Rotor- Quad copterRGB4Aphis gossypiiVision-based 	Walter Chivasa, et al., 2021 [33]	Maize	Multi-Rotor	Multispectral	6	Gemini virus	Visual Images
Gao, Junfeng et al., 2020 [35]PotatoMulti-RotorMultispectral6Phytophthora infestansVisual Images, Degree of SeverityDeng, Xiaoling et al., 2020 [36]LemonMulti-RotorHyperspectral4CandidatusLiberibacter 	Anton Louise P. de Ocampo and Elmer P. Dadios 2021 [34]	Solanummelongena	Multi-Rotor- Quad copter	RGB	4	Aphis gossypii	Vision-based Monitoring
Deng, Xiaoling et al., 2020 [36]LemonMulti-RotorHyperspectral4CandidatusLiberibacter asiaticusVisual inspection of imagesEverton Castel~aoTetila et al., 2020 [37]SoyaMulti-Rotor- Quad copterRGB4Defoliant pests such as insects and mollusksPest Segmentation and ClassificationVinr/cius Bitencourt Campos Calou et al., 2020 [38]BananaMulti-Rotor- Quad copterRGB4Yellow sigatokaVisual Images, Degree of SeverityDel Campo-Sanchez 	Gao, Junfeng et al., 2020 [35]	Potato	Multi-Rotor	Multispectral	6	Phytophthora infestans	Visual Images, Degree of Severity
Everton Castel~aoTetila et al., 2020 [37]SoyaMulti-Rotor- Quad copterRGB4Defoliant pests such as insects and mollusksPest Segmentation and ClassificationVinr/cius Bitencourt Campos Calou 	Deng, Xiaoling et al., 2020 [36]	Lemon	Multi-Rotor	Hyperspectral	4	CandidatusLiberibacter asiaticus	Visual inspection of images
Vinu'cius Bitencourt Campos Calou et al., 2020 [38]BananaMulti-Rotor- Quad copterRGB4Yellow sigatokaVisual Images, Degree of SeverityDel Campo-Sanchez et al., 2019. [39]GrapeMulti-RotorRGB4Cotton assidVisual inspection of imagesAbdulridha, Jaafar 	Everton Castel~aoTetila et al., 2020 [37]	Soya	Multi-Rotor- Quad copter	RGB	4	Defoliant pests such as insects and mollusks	Pest Segmentation and Classification
Del Campo-Sanchez et al., 2019. [39]GrapeMulti-RotorRGB4Cotton assidVisual inspection of imagesAbdulridha, Jaafar et al., 2019. [40]LemonMulti-RotorHyperspectral4Xanthomonas citriVisual inspection of imagesVanegas et al., 2018 [41]GrapeMulti-RotorRGB, Multispectral, Hyperspectral4GrapephylloxeraGround trapsand root digging, visual vigour assessments	Vinı'cius Bitencourt Campos Calou et al., 2020 [38]	Banana	Multi-Rotor- Quad copter	RGB	4	Yellow sigatoka	Visual Images, Degree of Severity
Abdulridha, Jaafar et al., 2019. [40]LemonMulti-RotorHyperspectral4Xanthomonas citriVisual inspection of imagesVanegas et al., 2018 [41]GrapeMulti-RotorRGB, Multispectral, Hyperspectral4GrapephylloxeraGround trapsand root digging, visual vigour assessments	Del Campo-Sanchez et al., 2019. [39]	Grape	Multi-Rotor	RGB	4	Cotton assid	Visual inspection of images
Vanegas et al., 2018 [41]GrapeMulti-RotorRGB, Multispectral, HyperspectralGround trapsand root digging, visual vigour assessments	Abdulridha, Jaafar et al., 2019. [40]	Lemon	Multi-Rotor	Hyperspectral	4	Xanthomonas citri	Visual inspection of images
	Vanegas et al., 2018 [41]	Grape	Multi-Rotor	RGB, Multispectral, Hyperspectral	4	Grapephylloxera	Ground trapsand root digging, visual vigour assessments

Table 3. UAV based remote sensing.

		Parameters					
References	Crop Name	Type of UAV	Camera	No. of Rotors	Pest Name	Observations	
Huang et al., 2018 [42]	Cotton	Multi-Rotor	Multispectral	4	Two-spotted spidermite	Damage assessments	
Samuel Joalland et al., 2018 [43]	Sugar Beet	Multi-Rotor	Hyperspectral	4	Beet Cyst Nematode	Visual Images	
Hunt et al., 2017. [44]	Potato	Multi-Rotor	Multispectral	6	Colorado potato beetle	Damage assessments	
Stanton et al., 2017 [45]	Sorghum	Fixed Wing	Multispectral	1	Sugarcane aphid	Arthropod counts	
Severtson et al., 2016a. [46]	Canola	Multi-Rotor	Multispectral	8	Green peachaphid	Arthropod counts, soil and plant tissue nutrient analyses	
Nebiker et al., 2016 [47]	Onion	Fixed Wing	Multispectral	1	Thrips	NA	
Ishengoma et al., 2021 [19]	Wheat	Multi-Rotor	RGB, Multispectral	4	Fall armyworm	Outbreak reported by grower	

Table 3. Cont.

A large volume of spatial images with high resolution was acquired with the UAV, which helps increase the accuracy level of the algorithm for classification and identification of the leaf spot in the banana. Quantification, prediction, identification, and classification are made to observe pests and insects in agricultural crops. The aerial images of the UAV and digital image processing (DIP), it calculates the severity of the attack of yellow Sigatoka. For estimating the damage in the field, it will act as an alternative method [38] Deep learning architectures are evaluated for the pest images of soybean and its classification obtained from the UAV. The performance of Inception-v3, Resnet50, VGG-16, VGG-19, and Xception was evaluated for different learning strategies with a dataset of 5000 images captured in actual field conditions [37].

UAVs mounted with traditional RGB cameras using remote sensing technologies could be considered to detect and quantify pests through UAV aerial images. Focusing on the 2D geomatic and 3D products, most of the users of UAV platforms need to improve the application utility and accuracy [39]. Recent advancement in remote sensing technology through unmanned aerial vehicles (UAVs) leads to rapid image processing tools for crop management and surveillance of pests. This UAV remote sensing-based technology increases the efficiency of existing practices of human surveillance for the detection of pests like grape phylloxera in vineyards. It uses UAV integrated with advanced digital hyper spectral, multispectral, and RGB sensors. The predictive model is developed for phylloxera detection. Under different levels of phylloxera infestation, the combination of RGB, multispectral, and hyper spectral images with ground-based data at two separate periods was explored [41] Comparing remote sensing technologies presented in Table 4.

Table 4. Aerial (manned aircraft) based remote sensing.

	Cron Name		Parameters	
Kererences		Camera	Pest Name	Observations
Xuan Li et al., 2021 [48]	alfalfa	Multispectral	Empoasca fabae	Damage assessments
Bhattarai et al., 2019 [49]	Wheat	Multispectral	Hessian fly	Arthropod counts
Backoulou et al., 2018a,b [50,51]	Sorghum	Multispectral	Sugarcane aphid	Damage assessments
Backoulou et al., 2016 [52]	Wheat	Multispectral	Greenbug	Arthropod counts or visual inspection
Elliott et al., 2015 [53]	Sorghum	Multispectral	Sugarcane aphid	Damage assessments

Deferences	Crop Name		Parameters	
Kererences	Crop Name	Camera	Pest Name	Observations
Backoulou et al., 2011a,b, 2013, 2015 [54–56]	Wheat	Multispectral	Russian wheat aphid	Visual inspections
Mirik et al., 2014 [57]	Wheat	Hyper spectral	Russian wheat aphid	Visual inspection of images
Reisig and Godfrey 2010 [58]	Cotton	Multispectral, Hyper spectral	Cotton aphid	Arthropod counts
Elliott et al., 2009 [59]	Wheat	Multispectral	Greenbug	Arthropod counts or visual inspection
Carroll 2008 [60]	Corn	Hyper spectral	European corn borer	Damage assessments
Elliott et al., 2007 [61]	Wheat	Multispectral	Russian wheat aphid	Proportion of infested plants
Reisig and Godfrey, 2006 [62]	Cotton	Multispectral, Hyper spectral	Spider mite	Arthropod counts
Willers et al., 2005 [63]	Cotton	Multispectral	Tarnished plantbug	Sweep net sampling
Fitzgerald et al., 2004 [34]	Cotton	Hyper spectral	Strawberry spider	Arthropod counts
Sudbrink et al., 2003 [64]	Cotton	Multispectral	Beet armyworm	Arthropod counts
F. W. Nutter Jr. et al., 2002 [65]	Soya Bean	Multispectral	Soya Bean Cyst Nematode	Visual inspection of images
Willers et al., 1999 [66]	Cotton	Multispectral	Tarnished plant bug	Sweep net sampling, drop cloth sampling
Lobits et al., 1997 [67]	Grape	Multispectral	Grape phylloxera	Root digging
Hart and Meyers, 1968 [68]	Citrus	Multispectral	Brown soft scale	Arthropod counts sooty mold assessments
Everitt et al., 1994 [69]	Citrus	Multispectral	Citrus blackfly	Visual inspections sooty mold assessments
Everitt et al., 1996 [70]	Cotton	Multispectral	Silverleaf whitefly	Visual inspections sooty mold assessments
Hart et al., 1973 [71]	Citrus	Multispectral	Citrus blackfly	Arthropod counts sooty mold assessments

Table 4. Cont.

Remote sensing data is used for studying the infestations of pests and insects in agricultural fields efficiently. In winter wheat (Triticumaestivum) fields in Kansas, USA, the association between Hessian fly (Mayetiola destructor) infestation and normalized difference vegetation index (NDVI) is evaluated using aircraft data and multispectral satellite. In each field, Hessian fly infestation was surveyed with multiple sampling points in a uniform grid fashion. The results have proven an increase in pest infestation with decreased NDVI in both aircraft and satellite data. NDVI satellite data performed better than NDVI aircraft data in pest infestation fields. The results show that remote sensing technology data can be used for monitoring the health of wheat plants and areas of poor growth [50]. Infestations of pests and insects in the agriculture field are not uniform and can proliferate in intensity and size. Remote sensing with multispectral data is used for assessing the sorghum fields for the infestations by sugarcane aphids. The difference in the normalized differenced vegetation index (NDVI) with bi-temporal images and analysis of changes in the image captured is efficient for assessing the infestation of temporal changes in the sorghum field by the sugarcane aphids. Experimentation on comparing changes in the field and distribution categories concerning normalized differenced vegetation index (NDVI) image classification from the sorghum field with infested sugarcane aphid, an essential technique for assessing the infestations of temporal changes by sugarcane aphids

Ma et al., 2019 [23]

Abdel-Rahman et al., 2017 [75]

Zhang et al., 2016 [76]

Lestina et al., 2016 [77]

Luo et al., 2014 [78]

Huang et al., 2011 [79]

Reisig and Godfrey, 2010 [59]

Reisig and Godfrey, 2006 [63]

in sorghum fields [72] Comparing orbital based remote sensing technologies presented in Table 5.

Wheat aphid

Stem borer

Oriental armyworm

Wheat stem sawfly

Wheat aphid

Aphid

Cotton aphid

Spider mite

References	Crop Name	Parameters				
Keletences		Camera	Pest Name	Observations		
MarianAdan et al., 2021 [73]	avocado	Multispectral	Persea mite	Visual Inspections		
Michael Gomez Selvaraj et al., 2020 [74]	Banana	RGB, Multispectral	Yellow sigatoka	Visual Inspections		
Bhattarai et al., 2019 [50]	Wheat	Multispectral	Hessian fly	Arthropod counts		

Multispectral

Multispectral

Multispectral

Multispectral

Multispectral

Multispectral

Multispectral

Multispectral

Table 5. Orbital (Satellite) based remote sensing.

Wheat

Corn

Corn

Wheat

Wheat

Wheat

Cotton

Cotton

Remote sensing tools coupled with Machine Learning have a lead role in monitoring the crop and surveillance of pests. Early warning systems use remote sensing applications to classify crops and pest-affected areas that provide accurate and cost-effective data at different agricultural fields with proper spatial, temporal, and spectral resolutions. However, monitoring more significant landscapes is challenging, therefore combining highresolution UAV satellite images of data through efficient machine learning (ML) models and advanced mobile applications, which helps detect the disease-affected part.

The hybrid model system is developed by combining a custom classifier and object detection model (RetinaNet) for disease classification and banana localization; we have used RGB-UAV aerial images from the Republic of Benin and DR Congo fields. This result proves better accuracy under different testing with performance metrics and reveals that RGB-UAV mixed model successfully classifies the object classification and detection among healthy and diseased crops with 99.4% accuracy. Thus, this approach provides high potential support systems for making major banana diseases in Africa [76].

Monitoring the pests and diseases makes vital in providing treatment practically in affected regions. The accuracy level of the crops affected by insects and pests gets improved when the environmental parameters are coupled with the vegetation index. Furthermore, similar symptoms can be identified for different pests and diseases in crop growth. Therefore, the information of growth period helps obtain the changes incurred in the crop concerning infection of insects and pests. An approach is developed by integrating environmental parameters and crop growth, experimenting with image performance classification effects, and discriminating the crops affected by the pests and diseases with Landsat-8 satellite images (Bi-Temporal).

The integrated model with environmental factors and temporal growth indices proved with good results of 82.6% accuracy. In addition, it performed better in discriminating damages using Landsat-8 satellite images in winter wheat crops. Further, to enhance the accuracy level of the advancement models by integrating multi-temporal remotely sensed data with multisource, which provides a detailed spatial crop pest and disease distribution to meet the current requirements of precision agriculture [23] Comparing ground based remote sensing technologies presented in Table 6.

Arthropod counts

Arthropod counts

Damage assess-counts

Arthropod counts
Arthropod counts damage

assessments

Arthropod counts

Arthropod counts

Arthropod counts

Rafarances	Cron Name		Parameters		
References	crop runie	Camera	Pest Name	Observations	
MaríaGyomar Gonzalez-Gonzalez et al., 2021 [80]	Citrus	Hyperspectral	Tetranychus urticae	visual inspection of the leaves	
Martin and Latheef 2019 [81]	Corn	Multispectral	Banks grassmite spotted spidermite	Damage assessments	
Alves et al., 2019, 2013 [82,83]	Soyabean	Hyperspectral	Soybean aphid	Arthropod counts	
Samuel Joall and et al., 2018 [43]	Sugar Beet	Multispectral, Hyperspectral	Beet Cyst Nematode	Visual Images	
Martin and Latheef, 2018 [84]	Pinto bean	Multispectral	Two-spotted spider	Controlled infestations	
Fan et al., 2017 [85]	Rice	Hyperspectral	Striped stem borer	Damage assessments	
Herrmann et al., 2017 [86]	Bean	Hyperspectral	Two spotted spider mite	Damage assessments	
Abdel-Rahman et al., 2013, 2010, 2009 [87–89]	Sugarcane	Hyperspectral	Sugarcane thrips	Arthropod counts, Damage assessments	
Mirik et al., 2012 [90]	Wheat	Multispectral	Russian wheat aphid	Visual inspections	
Zhang et al., 2008 [91], Luedeling et al., 2009 [92]	Peach	Hyperspectral	Spider mite	Arthropod counts, Damage assessments	
Fraulo et al., 2009 [93]	Strawberry	Hyperspectral	Two spotted spider mite	Arthropod counts	
Li et al., 2008 [94]	Sorghum	Hyperspectral	Corn leaf aphid	Arthropod counts,	
Xu et al., 2007 [95]	Tomato	Hyperspectral	Leaf miner	Damage assessments	
F. W. Nutter Jr. et al., 2002 [65]	Soya Bean	Multispectral	Soya Bean Cyst Nematode	Visual inspection of images	
Everitt et al., 1996 [70]	Cotton	Multispectral	Silverleaf whitefly	Visual inspections	
Peñuelas et al., 1995 [96]	Apple	Hyperspectral	European red mite	Arthropod counts	

Table 6. Ground based Remote Sensing.

Using spectral sensors with infrared range and 50 nm sensor bandwidth in soybean fields, a cumulative abundance of A. glycines could be effectively quantified. A. glycines on soybean are detected by simulating ground-based hyperspectral data with multispectral sensors. This approach reduces the complexity and cost while compared with counts of manual aphids with potential scouting of pests in soybean and crop production systems [82].

For the last few decades, most agriculture fields are using RS technologies for precision agriculture with different applications such as crop monitoring, Prediction of Yields, and Pest Management. Further, these techniques are also used for plant stress and nutritional deficiencies. RS technologies can detect pests and insects successfully in a wide variety of crops and fields. The average usage of different types of RS Platforms is shown in Figure 10. Precision Accuracy is more important in the economic development of the agriculture field, and the accuracy yields to monitor the crop infected by the pest and quality of the crop properly. Further, the precision accuracy rate in the agriculture field by RS technologies is shown in Figure 11.







Figure 11. Precision accuracy rate.

5. Economic Benefits of UAV Technologies

The UAV based remote sensing technology helps the farmers in the agricultural fields for gaining more productivity globally. There will be certain regions like South and Southeast Asia, Western and Central Europe, Central America and the Caribbean, and Southern Africa can be adapted with these kinds of new technologies without major human adaptations to increase productivity for a sustainable growing population.

There are more economic benefits for the society that could be derived from the remote sensing technology and unmanned aerial vehicle. Especially for developing countries like India and African countries, the usage of UAV leads to reduction in damage of crops and increase yields. If farmers can be encouraged to use this technology on the commercial side, it will eventually help them to increase the production of crops. Once the farmers are producing crops on a larger scale, it will help them to export the agricultural products to other continents. This will balance the problems in the economy of developing countries through an increase in export and reduction in import of agricultural produce to some extent. Moreover, it will gradually help increase employment which will reduce poverty and improve the standard of living for people.

6. Conclusions

Unmanned aerial vehicle in precision agriculture has critical challenges which are described as payload, Sensors used in the UAV, cost of UAV, flight duration, data analytics, environmental conditions, and requirements. Cost is the main challenge for UAV use, which is added with various needed sensors, mounting parts, technology-based applications, and the software needed for data analytics. Nowadays, commercial companies offer services

for renting out the various UAVs with all needed remote sensing devices. Data analytics is also a vital challenge to attain results at a periodic interval of time once the data have been collected from the various sensors mounted on the UAVs. It creates numerous terabytes of data stored, processed, and analyzed adequately with the appropriate software. Similarly, it is hard to develop a UAV that can detect both hotspots of the pest and the solutions applied for them since payload and flight duration are limited for UAV use in fields. Weather conditions such as rain, snowfall, clouds, and fog are another factor that limits the UAV activities and the sensing process. The farmers can easily adapt to this technology that is compatible with their agriculture requirements and cost-effective solutions.

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