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Unmanned Aerial Vehicles in Agriculture: A Review of Perspective of Platform, Control, and Applications

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ABSTRACT For agricultural applications, regularized smart-farming solutions are being considered, including the use of unmanned aerial vehicles (UAVs). The UAVs combine information and communication technologies, robots, artificial intelligence, big data, and the Internet of Things. The agricultural UAVs are highly capable, and their use has expanded across all areas of agriculture, including pesticide and fertilizer spraying, seed sowing, and growth assessment and mapping. Accordingly, the market for agricultural UAVs is expected to continue growing with the related technologies. In this study, we consider the latest trends and applications of leading technologies related to agricultural UAVs, control technologies, equipment, and development. We discuss the use of UAVs in real agricultural environments. Furthermore, the future development of the agricultural UAVs and their challenges are presented.

INDEX TERMS Agricultural applications, agricultural UAV, control technology, smart farming, unmanned aerial vehicle, UAV platforms.

I. INTRODUCTION

According to the 'Agriculture in 2050 Project,' the world population will reach about 10 billion by 2050. Consequently, food production will require a 70% boost [1]. To raise the food production rate, agriculture requires automation, robotics, information services, and intelligence that combines information and communication technologies (ICT), robotics, artificial intelligence (AI), big data, and the internet of things. Smart agriculture is an active field that produces new opportunities for the future.

At the center of the smart agriculture expansion are agricultural robots, among which, unmanned aerial vehicles (UAV) have been extensively applied [2]–[4]. UAVs have significantly reduced working hours, resulting in increased stability, measurement accuracy, and productivity. UAVs are not only less expensive than most other agricultural machines, but also they are easily operated. Moreover, their applications have contributed to the expansion of many areas of agriculture, including insecticide and fertilizer prospecting and spraying, seed planting, weed recognition, fertility assessment, mapping, and crop forecasting [5].

The market for agricultural UAVs is growing rapidly [7], and several venture companies have emerged. According to market research by Price-Waterhouse-Coopers, the market size of agricultural UAVs is forecasted to grow to about \$32.4 billion by 2050, accounting for about 25% of the global UAV market (see Figure 1) [8]. Major UAV companies include DJI, Parrot, Precisionhawk, AGEagle, and Trimble Navigation. Although various UAVs have been developed and commercialized, some challenges remain to be addressed for advanced agricultural solutions.

Leading technologies include precision positioning, navigation, controls, imaging, communications, sensors, materials, batteries, circuits, and motors. Depending on the use of the UAV and the characteristics of the farming sector, various technologies (e.g., equipment development, nozzle controls, and big data) are required. It is challenging to provide information about all UAV technologies. Therefore, in this paper, we focus on the development of robotic systems, sensors,

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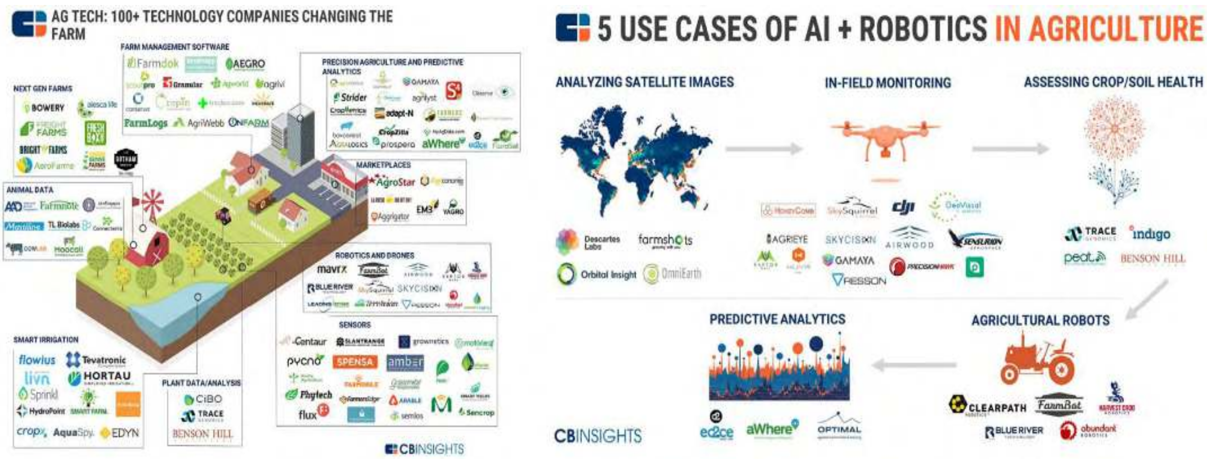


FIGURE 1. Major smart-agriculture enterprises [6].

and platform types, which are mainly examined in terms of research and development.

Like other industries, the agricultural sector has sought innovation by utilizing convergence technologies. UAVs have proven to be highly utilized throughout the sector. However, agricultural UAVs face numerous technical limitations, such as battery efficiency, low flight time, communication distance, and payload [9], [10]. Technical limitations must be solved to provide the right approach for the next generation of agricultural solutions. Thus, a plan and a system for future development should be established by first discussing the latest technologies, upgrades, precision instruments, and diversification. In this paper, we examine trends, the status, latest technologies, and utilization areas for agricultural UAVs and provide direction, prospects, and resolution tasks for the future.

The rest of this paper is organized as follows. Section 2 describes the leading trends in UAV development, including mounting equipment. Section 3 describes the primary control systems and the latest control system trends. Section 4 provides recent examples of real-world uses and describes areas where the future application is expected. Section 5 discusses UAV limitations, available applications, and current technology trends. The last section provides the conclusion.

II. AGRICULTURAL UAV PLATFORMS

UAVs are rapidly evolving in the field of agriculture, replacing satellites and other aircraft. When UAVs were first developed, they were widely used for military purposes and surveillance. UAVs can obtain high-quality images at low prices, whereas satellites and aircraft require high altitudes, cloud penetration, and other capabilities to enable clear photography. UAVs, on the other hand, fly at lower altitudes, allowing them to acquire clear images with ease. Thus, the number of UAVs used in agriculture is rapidly increasing. Platform types, controllers, sensors, and communication methods used in extant studies are summarized in Table 1.

A. PLATFORM TYPES

There are two primary types of UAV platforms: fixed- and rotary-wing (see Figure 2). A fixed-wing UAV is similar in appearance to an airplane. It flies via thrust and aerodynamic lifting force. A fixed-wing UAV is typically larger than a rotary-wing model and is used mainly for spraying and photography over a wide range [11]–[13]. Rotary-wing UAVs can be classified into helicopter and multi-rotor types. The helicopter type features a large propeller atop the aircraft. It is widely used for spraying and aerial photography [17]–[19], [39]. Multi-rotor models are named based on the numbers of rotors they possess, such as ‘quadcopter,’ meaning four rotors [20]–[22]. The hexacopter has six rotors [33], [34], and the octocopter has eight rotors [37].

The number of rotors corresponds to differences of payload and UAV size. Octocopters, helicopter types, and fixed-wing types have the largest payload capacities (9.5 kg) and are mainly used for spraying [37]. Quadcopters and hexacopters are relatively small and carry a smaller payload (1.25–2.6 kg). They are used for reconnaissance and mapping [21], [34]. Fixed- and rotary-wing UAVs have the largest payload (23 kg), followed by the helicopter-type (22 kg). Currently, fixed- and rotary-wing UAVs are increasingly being used for precision agriculture. Multi-rotor UAVs are used for extremely precise tasks, such as pollen–moisture distribution and precision control.

B. HARDWARE COMPONENTS

With UAVs, sensors and computing platforms are required, as shown in Figure 3. The sensors are usually installed into onboard computing platforms such as Arduino, Raspberry Pi, Orange Pi, Odroid, and Nvidia Jetson [17], [23], [24], [39], [40]. And also control platforms (i.e., control hardware) such as Pixhawk, Ardupilot, Multiwii, and Naza is connected with computing platforms. There is also a case some sensors (e.g., GPS receiver and IMU) are installed or connected to control platforms.

With the evolution of technology, sensors are getting smarter and lighter. Thus, their utilization has expanded to

TABLE 1. Platforms of agricultural UAV.

Platform (Payload)	Sensors	Communication	Reference
Fixed-wing (23kg)	GPS receiver Photodetectors	Wireless Radio	[11]
	Multi-spectral camera Hyper-spectral camera	Wireless Radio	[12]
	GPS receiver	-	[13]
	red–green–blue (RGB) camera	-	[14]
	RGB camera Thermal camera	-	[15]
	RGB Camera	-	[16]
Helicopter (22kg)	inertial measurement unit (IMU), RGB Camera	wireless local-area network	[17]
	Multi-spectral camera RGB camera	-	[18]
	IMU	Bluetooth	[19]
Quadcopter (1.25 kg)	RGB camera	-	[20]
	RGB camera Multi-spectral camera	-	[21]
	Visible-light camera Multi-spectral camera	-	[22]
	Thermal Camera	WiFi Wireless Radio	[23]
	Thermal camera	Xbee	[24]
	Hyper-spectral camera	-	[25]
	GPS receiver	Wireless Radio	[26]
	Thermal camera	Wireless Radio	[27]
	Multi-spectral camera Thermal camera	-	[28]
	RGB camera	WiFi	[29]
	RGB camera Thermal camera	-	[30]
	RGB Camera	Wireless Radio	[31]
	GPS receiver	-	[32]
Hexacopter (2.6kg)	RGB camera	-	[33]
	light detection and ranging (LiDAR), IMU RGB camera	-	[34]
	Hyper-spectral camera	Wireless Radio	[35]
	GPS receiver	Wireless Radio	[36]
Octocopter (9.5kg)	IMU, RGB camera	-	[37]
	IMU, RGB camera	-	[38]

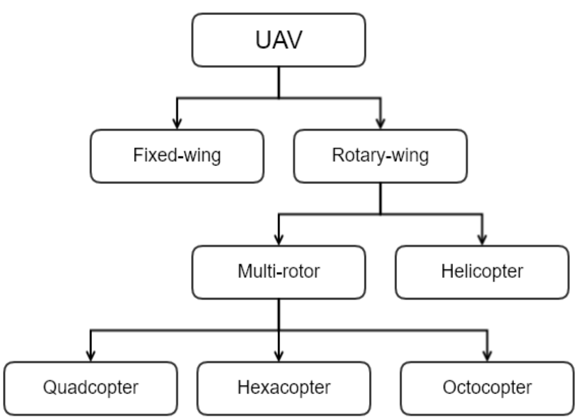


FIGURE 2. UAV platform types.

transportation, agriculture, and other fields. Global Navigation Satellite System (GNSS) is a receiver sensor-based localization and navigation system using satellites and it accurately reveals its UAV location. It can also serve as a safety-switch for arming. Real-time kinematics allows GNSS to be stream-lined for higher position accuracy (2–3 cm) and, typical GNSS examples include GPS in the US, Galileo in Europe, and GLONASS in Russia.

It is now possible to acquire essential agricultural information simply by capturing images. When using a visible-light camera, it is possible to obtain a clear resolution image, even from a long distance. Moreover, desired information can be obtained by using various camera types, such as a multi-spectral camera. Additionally, multi-thermal cameras are used to confirm the growth of crops and topography of rice fields. A LiDAR instrument rotates 360° to enable 3-dimensional (3D) mapping using a laser. LiDAR is an important sensor used for terrain reconnaissance and mapping [12], [15], [25], [26], [41].

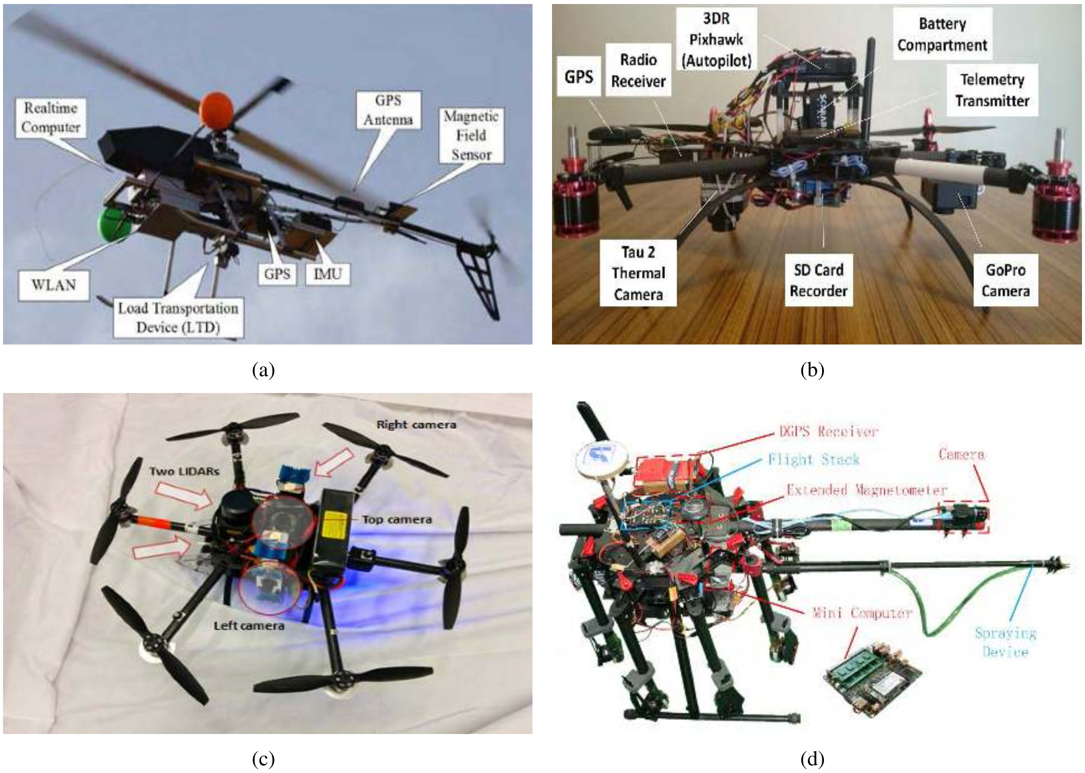


FIGURE 3. Multiple sensors attached to UAVs: (a) helicopter-type [17]; (b) quadcopter [27]; (c) hexacopter [34]; and (d) octocopter [37].

C. COMMUNICATION

MAVLink is a common communication protocol allowing to communicate UAV with ground control station (GCS). Physically, it is the communication between computing platform (e.g., Raspberry Pi,Arduino, and UDOO) or control platform (e.g, Pixhawk and Ardupilot) of UAV and application (e.g., mission planner and Qgroundcontrol) of GCS [42].

MAVLink transmits directions, GNSS position, and speeds of the UAV. The communication distance between the UAV and the GCS depends on specifications, but it can communicate up to 2 km when the UAV is within line-of-sight. Currently, UAVs are programmed to automatically return to its first position when communication is interrupted. This is the return-to-launch mode, which helps prevent accidents [16], [27], [28], [35], [38].

There are physical communication systems between the GCS and UAVs such as ZigBee, radio-frequency modules, and other transmitters. The communication distance can be increased with the addition of technologies, including phone apps. Additionally, current cellular technology is evolving from 4G to 5G, which promises to greatly improve communications and data-processing speeds, which will be useful for high-definition mapping [29]–[32], [36].

III. CONTROL OF AGRICULTURAL UAVS

Agricultural UAVs use a limited-capacity battery and do not run idle during flight. Accordingly, various studies have been conducted on control technologies used to maximize farming efficiency. Critical technologies for agricultural UAV control include flight technology (e.g., attitude and altitude controls, navigation systems, obstacle recognition and avoidance, decision-making and judgment, and large-scale control). There are also wireless tools for data communications with GCSs.

We next discuss the control technology of a quadcopter, which is the most well-known UAV. Controls can be categorized into three classes: linear, non-linear, and learning-based, as shown in Figure 4. We introduce standard control methods and study the latest trends of each control technology.

A. MODELING

Here, we describe the basic dynamic modeling of UAVs. We chose two UAV models: fixed-wing and quadcopter.

First, fixed-wing UAVs are shaped like airplanes, as shown in Figure 5. When a fixed-wing UAV runs on the runway quickly using engine power, the air comes towards the wings at a rapid speed. The approaching air flows up and down in the center of the wing, which in turn causes the air on the top to move faster and the bottom to move slowly. During this process, pressure differences occur, and lift forces are generated, causing the UAV to rise. After takeoff, the lift force must be maintained for the fixed-wing UAV to continue to fly. Only by flying above a certain speed can it generate airflow to generate a lift force. Therefore, it is impossible to vertically climb or descend and hover while flying.

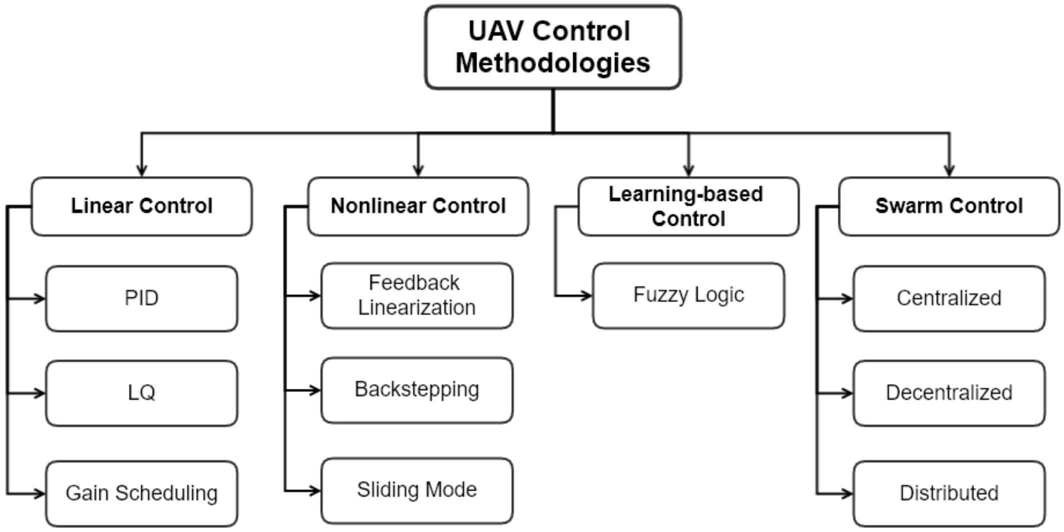


FIGURE 4. Classification of control methodologies for UAV control.

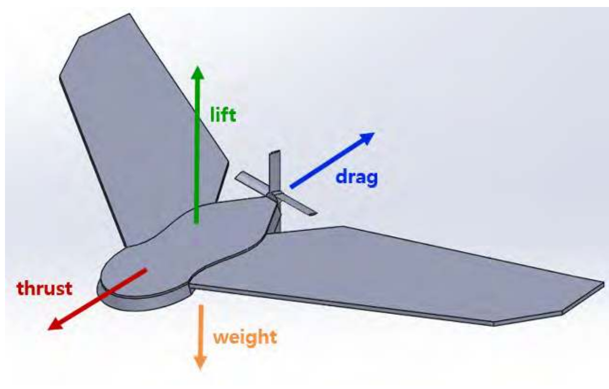


FIGURE 5. Fixed-wing UAV model.

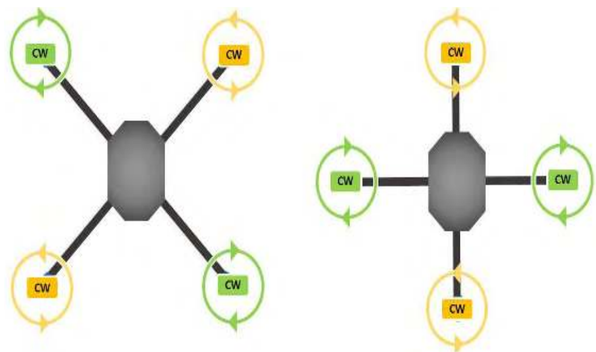


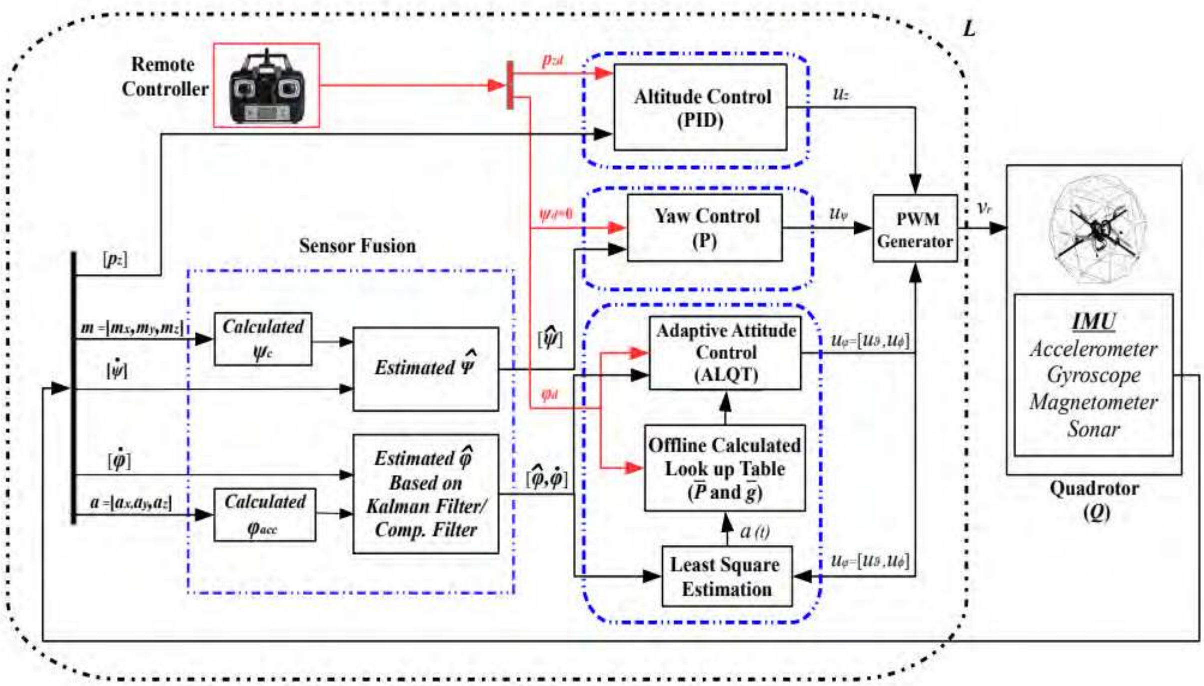
FIGURE 6. Quadcopter models: (left) cross-type (x) model; (right) plus-type (+) model.

Second, a quadcopter has four arms equipped motors and propellers. Two rotors turn in the clockwise (CW) direction, and the others turn in the counter-clockwise (CCW) direction. The attitude and movement are controlled by adjusting the relative speeds of the rotors. The rotors roll left and right, pitch backward and forward, and yaw CW and CCW when rotating around the x, y, and z-axes, respectively. Quadcopters can be divided into cross- and plus-types, as shown in Figure 6.

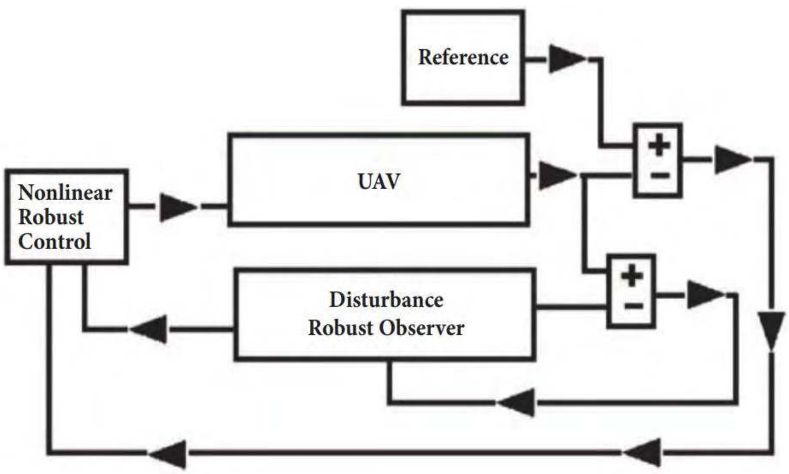
When moving forward, a cross-type quadcopter reduces the output of the two motors located at the front and increases the output of the two motors at the rear, causing it to tilt forward and move. If only pitch or roll controls are applied, the output of all motors changes and the response is fast and stable. However, if the pitch and roll are operated simultaneously, the output of one motor is significantly reduced, whereas that of the others is significantly increased. Therefore, the reaction is relatively slow when the movement occurs in an oblique direction.

A plus-type quadcopter significantly reduces the output of the motor located in the front, whereas it significantly increases that of the one located in the rear, tilting forward and flying. Contrasting a cross-type quadcopter, the response when only one key is operated is rather weak, because the output of only one corresponding pair of motors changes, whereas that of the other pair remains the same. Alternatively, when a pair of motors is operated independently with one button, the movement becomes intuitive. Plus-type quadcopters are not widely used, because they take longer to operate with only one key than when two keys are operated simultaneously. Additionally, because of their structure, their wings can block the cameras.

Finally, studies deviating from conventional UAVs are underway as shown in Figure 8. In [45] and [46], a fully-actuated hexarotor UAV with tilted propellers and an omni-directional aerial robot was developed. Recently, novel mechanisms and modeling have been developed to increase UAV maneuverability and scalability, such as with a passive rotating shell [47], an interacting-boomcopter [48], a long-reach aerial manipulator [49], an agile single-engine holonomic multicopter [50], an aerial blimp robot [51], a hybrid UAV [52], and a transformable hovering rotorcraft [53]. When these forms are applied to agriculture, their utility and usefulness can be further expanded.



(a)



(b)

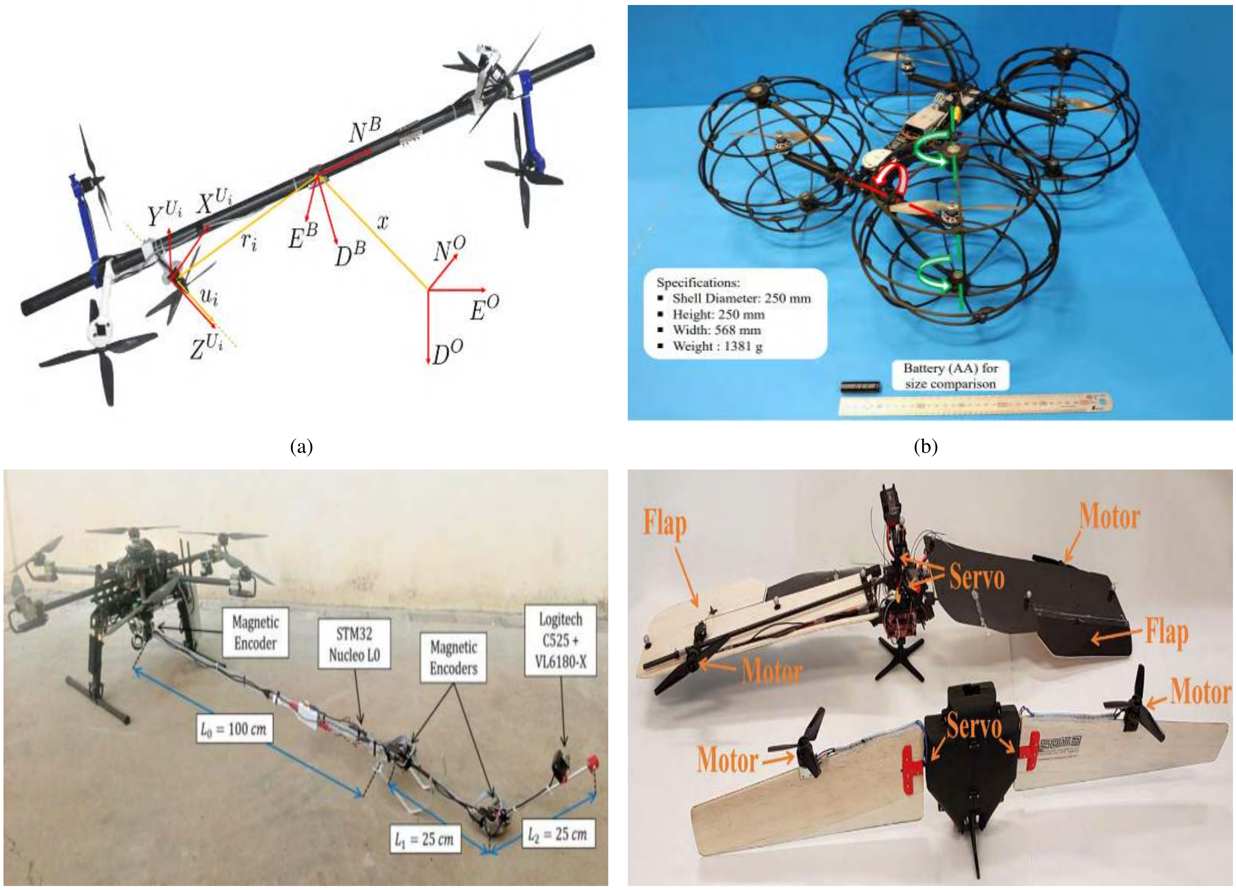
FIGURE 7. UAV Controllers: (a)linear control [43]; (b)non-linear control [44].

B. CONTROL

UAV models vary in weight and control and are constrained by weather conditions. On windy days, a UAV can overturn. Linear and non-linear controls, such as those as shown in Figure 7, are used to control UAVs and handle wind and weather, except for rain and snow. Under both linear and non-linear systems, a UAV can remain stable, because controls exist to provide countermeasures against gusts. Generally, linear and non-linear controls are classified based on whether they follow the principle of superposition. In the case of non-linear control, there is a change with time that does not exist with linear controls.

Generally, a system based on linear quadratics (LQ) is used to provide stable controls for agricultural applications. A LQ-based control method provides robust and precise steady-state tracking. Additionally, LQ and gain scheduling are easy to design and configure. The constant feedback control gain is computationally intensive and is, therefore, used in real-time programs. Another method of communication and control entails reducing noise by adding Kalman and particle filters. Simulation tools, such as MATLAB and LabVIEW, can also be used to model and evaluate stability and performance [43], [56]–[58].

Non-linear controls are used for wind storms, as mentioned. Feedback linearization, backstepping, and to apply non-linear controls. Feedback linearization involves converting non-linear systems into equivalent linear systems by changing variables and appropriate control inputs.



(a) (b) (c) (d)

FIGURE 8. Various types of UAV models: (a) Omni-directional UAV [46]; (b) UAV with rotating shell [47]; (c) long-reach aerial manipulator [49]; (d) transformable hovering UAV [53].

Backstepping refers to stabilizing an unstable system. Sliding mode runs continuously along the normal cross-section of the system. Non-linear controls incorporate attitude-control rules and input signals (e.g., altitude, roll, pitch, and yaw). Compared to a typical wireless controller, it can operate at high speeds and perform well in noisy environments.

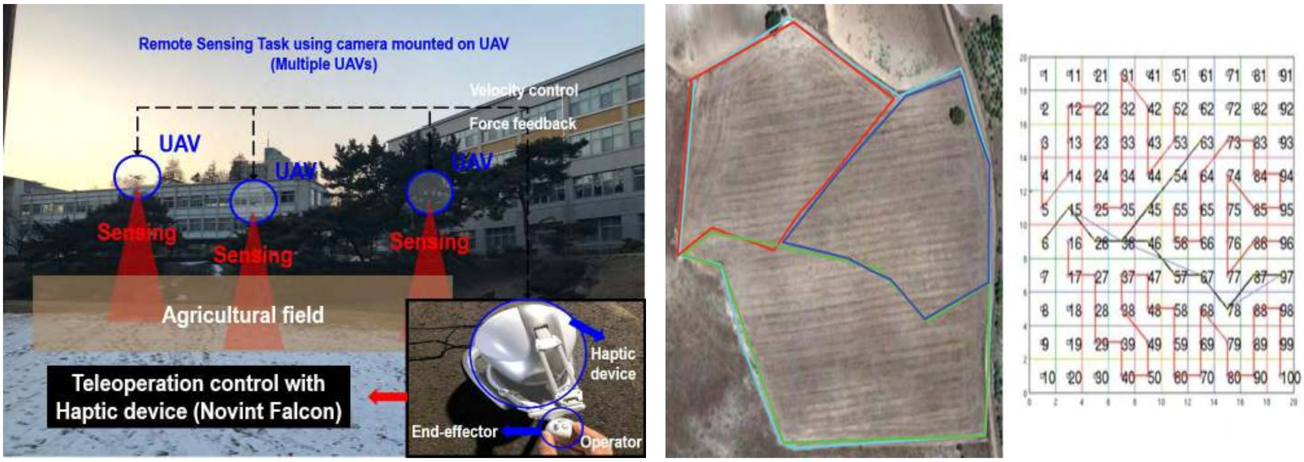
Non-linear controllers are designed using the most basic approaches to flying: altitude, roll, pitch, and yaw. Thus, the UAV does not automatically follow the wind direction. Major adjustments are required, depending on the payload. If the non-linear control system is well designed, one can steer the UAV without redesigning it. This capability has been used by many researchers and farmers. Linear and non-linear controls are mainly used with quad-cores, commonly used for agriculture, mapping, and photography. Research on linear and nonlinear controls is continuing [44], [59], [60].

There are also learning-based control methods applied to UAVs. Learning-based controls do not require dynamic models and can be learned using the data obtained from flights. These controls are largely used as a type of fuzzy logic that divides ambiguous situations into approximations. Various conditions are learned from flight data, and accordingly, flights are conducted again. This type of control has been successfully validated in experiments, a model-less approach allows it to be used in other quadcopter configurations. However, uncertainty remains about its stability and robustness. Thus, additional testing is required [59].

C. TASK ALLOCATION & SWARM CONTROL

Scant research has addressed the range and physical fatigue of the operator in the context of limited UAV flight time and payload. Researchers have started considering this problem, however, when evaluating the simultaneous control of multiple UAVs. Swarm control is a very practical technology that controls multiple UAVs via one operator or program. Swarms can be centralized, decentralized, and distributed according to its desired shape. It is possible to select and apply an efficient shape according to the application.

The most important aspect of this technique is the combination of algorithms required to maintain consistent distances between UAVs. Linear and nonlinear controls that resist strong external influences are required. The use of swarm technologies in agriculture is shown in Figure 9. It will likely improve the accuracy of agricultural operations, reduce work time, reduce operator control efforts, and address battery and payload shortages.



(a) (b)

FIGURE 9. **(a) Swarm control [54]; (b) task allocation [55].**

These issues and route planning must be further developed [54], [61]–[63].

Using swarm control, a route is assigned to each UAV. The subdivision of tasks and paths is called 'task allocation.' Task-allocation technology is currently used to map agricultural lands. With satellites, it is possible to obtain a map at once by capturing a single picture. However, it is inefficient in terms of cost. To compensate, a camera sensor is attached to a UAV to create a map, as shown in Figure 7. Because a wide range of images must be taken several times, a route is built by dividing each region among several UAVs.

This technique requires an algorithm to prevent collisions and another to map the allocated zones. The K-means algorithm can be used for this. This algorithm allows negotiations among UAVs, reducing complexity. Currently, various simulations and experiments using UAVs and unmanned ground vehicles (UGV) are in progress [14], [55], [62].

IV. APPLICATIONS OF AGRICULTURAL UAVS

Currently, agricultural UAVs perform numerous tasks in various working environments. They are used in rice paddies, fields, and orchards, and the demands are steadily increasing. This section introduces the applications of current agricultural UAVs, as summarized in Tables 2 and 3. The task periods in the tables are defined as the times spent doing actual farm work.

A. MAPPING

2D or 3D maps of an agricultural field made by UAVs can provide useful information. For example, the area of the farmland, soil conditions, and status of the crops can be used model enhancements and efficiencies [67], [91]. Therefore, mapping research continues to draw attention.

[64] obtained high-resolution maps delineating the spatial variations of radiation interception using UAV images (see Figure 10). The generated maps allow for profitable precision agriculture tasks, such as the agronomic control of homogeneous zones and the separation of fruit quality areas.

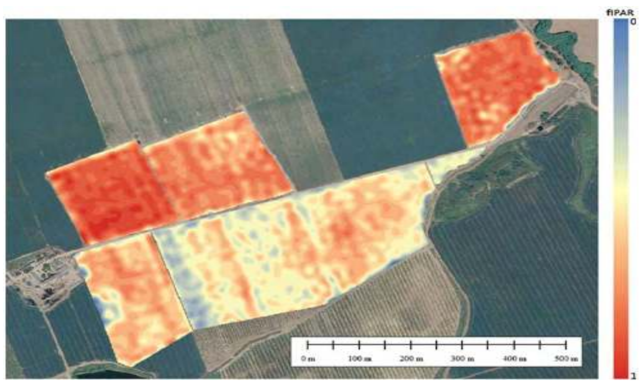


FIGURE 10. **Maps obtained for citrus and peach orchards showing the variation of vegetation cover [64].**

B. SPRAYING

Compared to a speed sprayer or a wide-area sprayer, UAVs can reduce pesticide use and maximize efficiency [92], [93]. The measure of pesticides per hectare of farmland correlates to the risks of worker ailments and environmental pollution. An UAV can minimize pesticide use. This strategy achieves large-scale decontamination of up to 50 ha per day and requires only about 10 min of work per 0.5 ha area. Thus, UAV research seeks to reduce labor requirements.

[73] studied citrus farms to determine the optimum level of preventive work by spraying them from various heights using a UAV. [70] studied algorithms that automatically planned and performed optimal flights using MSP430. A single microchip was attached to the UAV to maximize the efficiency of the cleanup operation. Studies have also been conducted to improve accuracy of control over crops by developing precision control algorithms [94].

DJI, which has a large share of the UAV market, launched the MG-1 model for spraying pesticide. MG-1 is equipped with eight rotors, has a 10kg payload, and can spray up to 4 ha per hour. MG-1 automatically adjusts the amount of pesticides according to the flight speed to maintain a constant

TABLE 2. Applications of Agricultural UAVs.

Task	Model	Indices	Crop	Sensors		Flight Altitude (m)	Task Period	References
				Type	Model			
Mapping	Fixed-wing UAV	Normalized Difference Vegetation Index (NDVI)	Peach, Citrus	Multi-spectral camera	Tetracam MCA-6	150	Summer	[64]
	Helicopter	NDVI	Wheat	Multi-spectral camera	Tetracam MCA-6	15–70	August–September	[65]
	RC airplane	Tree canopy, Density	Palm-oil, Sugar cane, Teak wood	Digital camera	Canon CHDK	100–400	Summer	[66]
	Quadcopter	Normalized Green–Red Difference Index (NGRDI), ExG, CIVE, VEG, ExGR, COM, WI	Wheat	Digital camera	Olympus PEN E-PM1	30, 60	Winter	[67]
		Root-Mean Squared Error	Wheat	Multi-spectral camera	Olympus EP-1	30, 60, 100	Spring–Summer	[20]
		Object-Based Image Analysis (OBIA)	Weed	Digital camera	Tetracam MCA-6	30	Winter	[68]
Spraying	Helicopter	Spray work rate	Vineyard	Digital camera	-	3–4	May	[69]
		Route precision, Spraying uniformity	Wheat	Image transmitter	-	5, 7, 9	Summer	[70]
		Droplet size, Flow rate	-	Proprietary radio receiver	-	6	Throughout the year	[71]
	Quadcopter	Time of communication between a sensor	Soy, Rice, Corn, Gapes, Sugarcane	RF module	XBee-PRO series 2	5, 10, 20	Summer	[72]
		Droplet coverage rate, Density, Droplet size	Cocktail Grapefruit, Citrus	Digital Plant Canopy Imager	Camas CI-110	3.5, 4, 4.5	Spring–Summer	[73]
		Observed Deposition Rate, Field Work Rate	-	Multi-spectral camera, Hyper-spectral camera, Near-inrared, Color-infrared	-	Few meters	Throughout the year	[74]
Crop Monitoring	Fixed-wing UAV	Spectral index (ch3/ch2)	Coffee	Multi-spectral camera, Digital camera	DuncanTech MS3100, Hasselblad 555ELD	6400	Autumn	[75]
	Hexacopter	Blue Green Pigment Index 2 (BGI2), Reformed Difference Vegetation Index (RDVI)	Barley	Hyper-spectral camera	Firefly ultra-high definition 185	30	Summer	[76]
	Quadcopter	NDVI, Ontario Soil and Crop Improvement Association	Soybean, Wheat, Barley, Oat, Canola	Digital camera	Aeryon Photo3S	120	Spring–Autumn	[77]
		Visible-band Difference Vegetation Index, Normalized Green-Blue Difference Index, Green-Red Ratio Index	Wheat	Digital camera	SONY ILCE-6000	100	September–July	[78]

continuous dose, using the smallest amount. Furthermore, microwave radar sand flight control systems can be integrated to scan the terrain in real time, automatically measuring distances within the crops in centimeters. MG-1 maintains a constant concentration of spray, regardless of ground height. The MG-1P is equipped with a wide-angle lens with a viewing angle of 123° to detect remote bypass paths at once. Compared to the MG-1, the MG-1P can control five gases with one controller, increasing UAV efficiency and ensuring suitability for a wide range of farm types.

C. PLANTING

It is no surprise that planting can be made more efficient using UAVs. Advantages include making it possible to work on a large area of uneven rice paddies [47]. A system is used to distribute seeds and plant nutrients when sowing to provide perfect conditions for plant growth. Although the use of UAVs for planting is still in development, it is expected that this strategy will produce efficient work, provided the UAV is equipped with image recognition technology and optimized planting tasks.

D. CROP MONITORING

Crop monitoring is the work conducted to predict the yield or quality of a crop via analysis of crop data. Crop monitoring is essential for optimal crop production. However, monitoring a large farm requires significant time and labor. Very large farms are often monitored via satellite. However, this is not suitable for precision crop monitoring. Crop monitoring via UAVs has been proposed for this. Thus, high-resolution data has been obtained, and weather effects have been reduced.

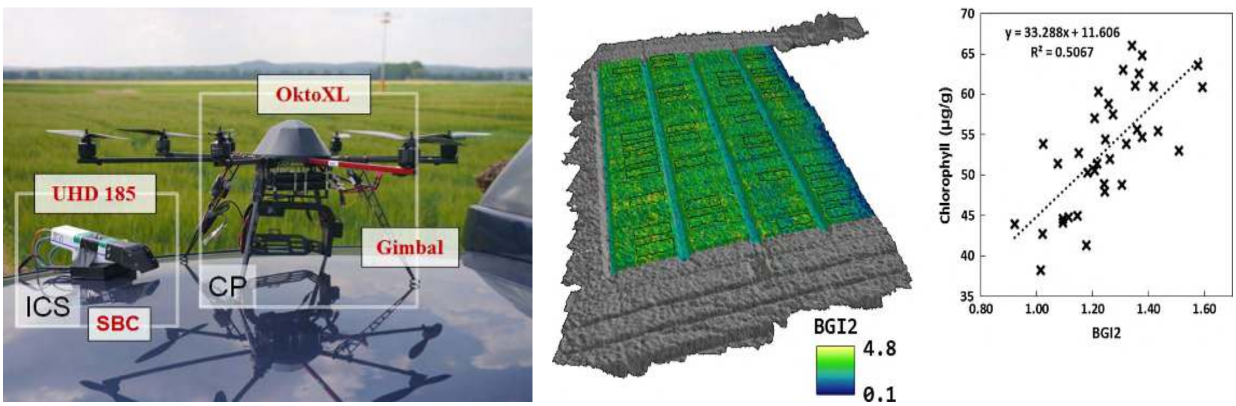
[76] performed a study to apply 3D data collected from lightweight snapshot cameras attached to aerial vehicles (see Figure 11). Because the sensors used are lightweight, low-flying UAVs can monitor crops at a low cost. Studies have also been conducted [95] to analyze the vegetation index of grapes by acquiring data from vineyards using multi-spectral cameras. These vegetation index data provide important indicators of improvement and productivity.

E. IRRIGATION

An UAV equipped with multi-spectral cameras and heat sensors can identify areas where water is scarce, as shown

TABLE 3. Applications of agricultural UAV.

Task	Model	Indices	Crop	Sensors		Flight Altitude (m)	Task Period	References
				Type	Model			
Crop Monitoring	Octocopter	NDVI, Soil Adjusted Vegetation Index (SAVI), Optimized SAVI (OSAVI) Named by the developers Gnyp and Li	Barley	RGB-sensor	Panasonic Lumix GX1	50	April–July	[79]
Irrigation	Fixed-wing UAV	Near Infrared Domain (NIR), Red domain (R), NDVI	Grape fruit, Mandarin	Digital camera	Canon IXUS 125 HS	100	Summer	[80]
		Crop Water Stress Index, Transformed Chlorophyll Absorption in Reflectance, Photochemical Reflectance Index, NDVI	Vineyard	Multi-spectral camera	Tetracam MCA-6	200	Summer	[81]
		Blue/Green Indices, NDVI, RDVI	Blanco, Almond, Peach, Lemon, Orange	Micro-hyperspectral camera	Headwall Photonics Micro-Hyperspec visible NIR	575	Summer	[82]
		Water Deficit Index, Land Surface Temperature, NGRDI	Barley	Digital camera	Optris PI 450	90	Spring–Summer	[83]
	Quadcopter	Difference Vegetation Index (DVI), NDVI, Modified SAVI (MSAVI), OSAVI	Vineyard	Multi-spectral camera	Parrot SEQUOIA	30	June–August	[84]
Diagnosis of Insect Pests	Fixed-wing UAV	NDVI, Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Red Edge Index (NDRE)	Potato, Barley	Multi-spectral camera	Canon S110 NIR, multiSPEC 4C	-	May–July	[85]
	Hexacopter	OSAVI, Phylloxera Index (PI)	Vineyard	High resolution RGB camera, Multi-spectral camera, Hyper-spectral sensor	Canon 5DsR, MicaSense RedEdge, Headwall Nano-Hyperspec	60, 100	December–February	[86]
		NDVI, GNDVI, SAVI	Citrus	Multi-spectral camera	Tetracam MCA6	100	Winter	[87]
Artificial Pollination	Helicopter	Pollen directions of X, Y and Z	Rice	Wind speed sensor	-	1.15, 1.23, 1.33	April	[88]
	Hexacopter	Pollination rates	Apple, Almonds, Cherries, Pears	-	-	Few meters	Aprill–May	[89]
	Quadcopter	Pollen collection efficiency	Tulipa gesneriana	High-definition digital camera	-	Contact with target	April–May	[90]



(a) (b)

FIGURE 11. **(a) UAV platform; (b) spectral sample areas marked with black rectangles and averaged BGI2 values per plot [76].**

in Figure 12. [96] conducted a study using electromagnetic spectrum sensors with RGB and NIR cameras to obtain data for water management and irrigation control. The authors experimented using multiple UAVs to maximize irrigation effects. Most studies have focused on image processing and data acquisition. However, some have performed irrigation work where water is scarce by loading water instead of pesticides. With future smart farming, an irrigation automation system will be applied efficiently using a collaborative system integrating UAVs, UGVs, or swarms.

F. DIAGNOSIS OF INSECT PESTS

In the United States, approximately $33 billion of annual damage is caused by pest infestations and infections [97]. Early diagnosis is essential because damage spreads quickly. [85] conducted a study in which high-resolution RGB cameras and multi-spectrum sensors mounted on UAVs

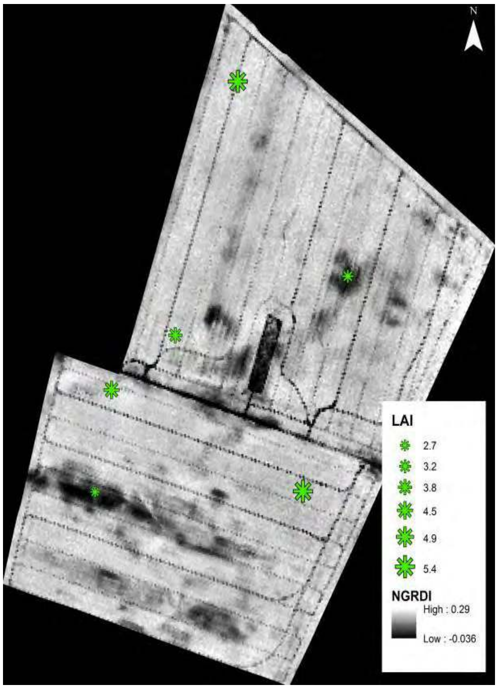


FIGURE 12. Location and size of the leaf-area index measurements on an NGRDI map [83].

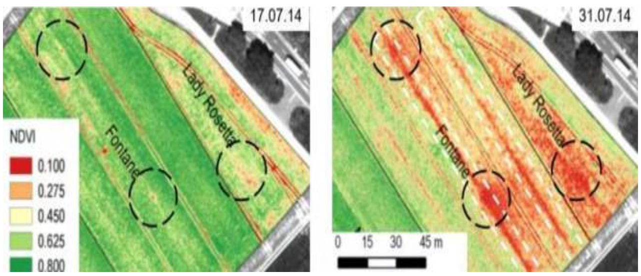


FIGURE 13. Detailed view of a potato field NDVI map, highlighting the three original sites of potato blight (dotted circles) and the subsequent spread [85].

were combined to examine potato fields for infection (see Figure 13). They showed accurate and fast pathogen detection using high-quality spectral measurements.

G. ARTIFICIAL POLLINATION

As the population of honeybees continues to decrease worldwide, research on a robot pollinator has gained traction. Thus, the National Institute of Advanced Industrial Science and Technology (AIST) has developed a small UAV for pollination, as shown in Figure 14 [90]. The robot uses animal hair coated with gel to carry pollen. AIST plans to integrate AI, GPS, and cameras with these UAV robots.

Pollination has also been carried out using the wind power generated from UAVs, rather than by direct contact. [88] conducted a study on how the helicopter-type UAV wind power influenced the distribution of rice pollen. Specifically, they found that the wind field created by UAV exerted an asymmetrical influence on pollen distribution.

FIGURE 14. (a) Vertically aligned animal hairs on a tape with an ILG coating; (b) ILG-coated animal-hair-modified artificial pollinator [90].

V. DISCUSSIONS

Issues, such as the aging rural population, self-sufficiency, and declining labor force, constantly require innovation. Although using a robot typically has limitations, there are many approaches to solve them. In this section, we discuss the limitations of current UAVs, identify a more scalable agricultural application, and, finally, present the latest research trends.

A. LIMITATIONS

A major problem with UAVs is battery and flight time limitations. To solve this, research on battery technology continues. Currently, we use lithium-ion batteries. Their capacity is larger than that of conventional batteries. However, the larger the capacity, the heavier the weight. This issue cannot currently be solved. Although battery management requires constant maintenance, most UAV operators do not pay attention.This causes increased periodic replacement, resulting in additional costs. Currently, it is possible to fly 20–30 min with a fresh battery. However, this does not provide enough time for serious crop work. Researchers are developing optimized hybrid battery solutions as a consequence [103]–[105].

Researchers are also studying swarm-control techniques that use multiple UAVs to efficiently perform a wide range of tasks. Swarms provide practical techniques to lower battery costs and operate more efficiently with shorter flight times.

There are needs to develop a novel (i.e., ergonomic, user-friendly, and human-centered) GCS. An improvement of user interface is also demanded by considering multimodal feedback such as visual, haptic, and auditory feedback. Normal people in agriculture typically have difficulty operating UAV. Usually, only experts use UAV to perform agricultural tasks. Furthermore, it is necessary to lower the entry barriers associated with the accessibility of agricultural UAV. Improving the user interface can help users who are older or unfamiliar with UAV to control the UAV more easily. More specifically, human-centered user interface and feedback are efficient to deal with multi-UAV systems [106].

B. AVAILABLE APPLICATIONS

Early UAV-based smart farming applications used relatively simple sensors, such as controls and monitors, and the use was not extensive. However, various sensors can be developed

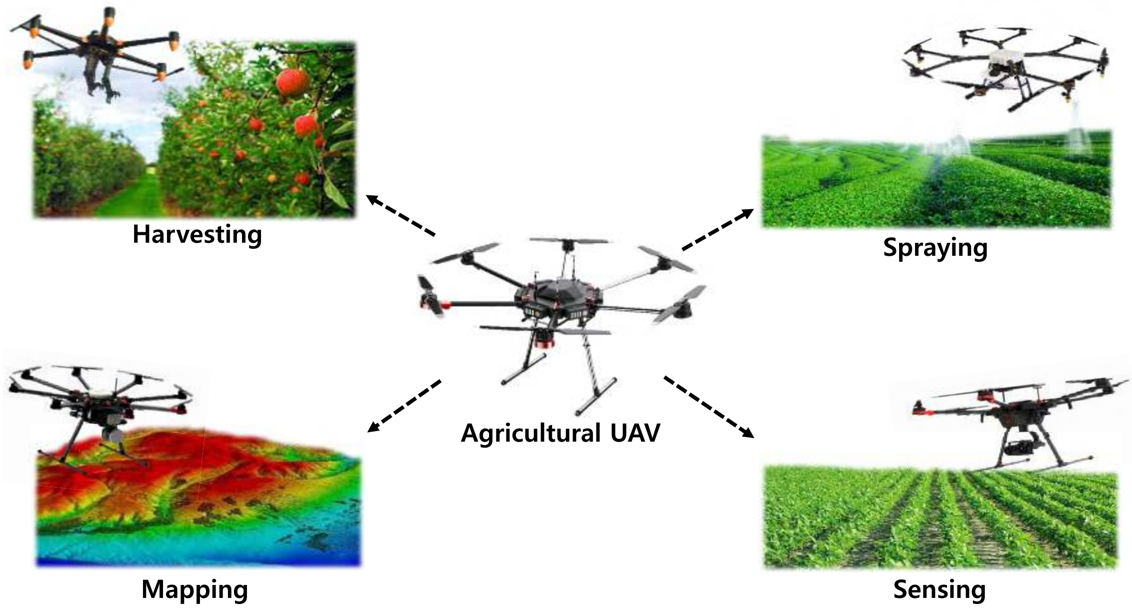


FIGURE 15. Multiple types of agricultural UAVs: harvesting UAV [98], spraying UAV [99], conventional UAV [100], mapping UAV [101] and sensing UAV [102].

and installed, as shown in Figure 15. UAVs are not currently used for harvesting. However, they will likely be in the future, as shown in Figure 15(a).

Mapping extends beyond field topology. It also allows AI learning and recognition for smart agricultural applications. Weed (treatment) maps, for example, provide operators a means to monitor spraying in real time. Rice and field farming can then be harvested simultaneously. However, for orchards, the yield depends on degrees of ripeness. By combining various tasks with software, we continue to advance deep learning and robotics toward harvesting work [107], [108].

Smart agriculture can be used anywhere in the world. Sub-Saharan Africa has begun to utilize smart agriculture with UAVs to improve major crops. Furthermore, it allows farmers to generate more production from smaller farms. Thus, people who have performed traditional agriculture are becoming familiar with smart agriculture by using UAVs [109], [110].

C. LATEST TECHNOLOGY TRENDS

UAV technology grows fast. Communication speeds have improved drastically. Data-processing speed has vastly improved. With the increase in communication range, the reach of a worker's control is extended [111].

Currently, simultaneous localization and mapping (SLAM) technology, which leverages autonomous driving, is being used with UAVs and UGVs. SLAM technology maps in real time using a camera and/or LiDAR. It recognizes its own position and identifies obstacles, while autonomously traveling or performing tasks. The technology does not require the use of existing controllers, and it is efficient and practical, because it works autonomously. With these developments, we arrive closer to smart agricultural capabililty [112], [113].

Development of soft grippers has made it possible to test harvesting. It is nowhere near perfect, but the tools and techniques are improving. Soft grippers can be attached to robotic arms on a UAV. Then, a camera attached to the gripper can be used to learn and control the harvesting actions [114]. With swarm-control techniques, UAV and UGV teams are being studied for combined agricultural tasks. Over the next few years, multi-robot technology will likely be possible [54].

VI. CONCLUSION

Agricultural UAVs show unlimited potential in agriculture. However, there remain many limitations and challenges in these early stages of research and development. In this paper, we review the platforms, control, and applications of agricultural UAVs that have been developed or understudy. Besides, various limitations, available applications, and the latest trends of agricultural UAVs are introduced to describe the direction of future research.

To be more specific, first, we reviewed the hardware configurations of UAVs for agricultural use (i.e., platform types, components/sensors, and communication). We also introduced the modeling, control systems, and control (i.e., linear, non-linear, learning-based, and swarm) for operating agricultural UAV. Thirdly, the application of agricultural UAV such as mapping, spraying, planting and monitoring was rigorously investigated, and classified. Finally, we discussed in-depth about the limitations (e.g., battery, multiple UAVs, and user interface), available applications (e.g., harvesting, AI-based precision mapping, and developing countries), and technology trends (communications, SLAM, aerial manipulator, and multi-robot systems). Here, we described a multi-robot system as a way to solve challenges and limitations for the robot-based smart farming system.

In summary, we present a detailed review of the agricultural UAVs which have outstanding utilization and potential. Therefore, this paper contributes to the future researches, markets, and applications of agricultural UAVs.

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