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Quadcopters in Smart Agriculture: Applications and Modelling

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Abstract: Despite technological growth and worldwide advancements in various fields, the agriculture sector continues to face numerous challenges such as desertification, environmental pollution, resource scarcity, and the excessive use of pesticides and inorganic fertilizers. These unsustainable problems in agricultural field can lead to land degradation, threaten food security, affect the economy, and put human health at risk. To mitigate these global issues, it is essential for researchers and agricultural professionals to promote advancements in smart agriculture by integrating modern technologies such as Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Wireless Sensor Networks (WSNs), and more. Among these technologies, this paper focuses on UAVs, particularly quadcopters, which can assist in each phase of the agricultural cycle and improve productivity, quality, and sustainability. With their diverse capabilities, quadcopters have become the most widely used UAVs in smart agriculture and are frequently utilized by researchers in various projects. To explore the different aspects of quadcopters' use in smart agriculture, this paper focuses on the following: (a) the unique advantages of quadcopters over other UAVs, including an examination of the quadcopter types particularly used in smart agriculture; (b) various agricultural missions where quadcopters are deployed, with examples highlighting their indispensable role; (c) the modelling of quadcopters, from configurations to the derivation of mathematical equations, to create a well-modelled system that closely represents real-world conditions; and (d) the challenges that must be addressed, along with suggestions for future research to ensure sustainable development. Although the use of UAVs in smart agriculture has been discussed in other papers, to the best of our knowledge, none have specifically examined the most popular among them, "quadcopters", and their particular use in smart agriculture in terms of types, applications, and modelling techniques. Therefore, this paper provides a comprehensive survey of quadcopters' use in smart agriculture and offers researchers and engineers valuable insights into this evolving field, presenting a roadmap for future enhancements and developments.

Keywords: quadcopters; smart agriculture; modelling; agricultural applications

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1. Introduction

The growing global population is making it extremely challenging to meet human needs for food and resources. As a result, the agriculture sector has become one of the most critical sectors in every country, requiring continuous development to address this gap while simultaneously boosting economic growth [1,2].

The agriculture sector has evolved significantly over the years, shifting from labor-intensive methods to technology-driven practices. Traditional agriculture relied heavily on manual labor, animal power, and conventional tools. Over time, farmers began to adopt more advanced machinery, chemical fertilizers, and pesticides, which increased field productivity [3,4]. In the late 20th century, new technologies, such as satellite imaging, were introduce to monitor crop fields through multispectral images [4,5].

However, despite these advancements, the agriculture sector continues to face many challenges worldwide, including desertification, water scarcity, pollution, and the excessive use of chemicals and resources [6]. To address these issues, smart agriculture emerged in the early 21st century, focusing on optimizing resource use and improving both the quality and quantity of agricultural output. In this modern phase, new technologies like Artificial Intelligence (AI), IoT, and UAVs are integrated into the agriculture sector to make it smarter and more efficient [4,7–10].

UAVs are among the modern technologies being extensively used in smart agriculture due to their flexibility, autonomous operation, cost-effectiveness, ability to avoid certain adverse weather conditions, and capacity to complete agricultural missions efficiently and in less time. Playing a significant role in smart agriculture, UAVs have captured researchers' interests, as they are considered essential tools for monitoring vast areas and performing precision appplications [11–14].

Among the various types of UAVs, this paper focuses on rotary-wing UAVs, specifically quadcopters, due to their multiple capabilities and features, such as agility, ability to hover, ease of use, and more. Quadcopters surpass other UAVs and are the most commonly chosen and popular drones in various fields [15–17], including academic projects, agricultural applications, military purposes, entertainment, and more, as illustrated in Figure 1.

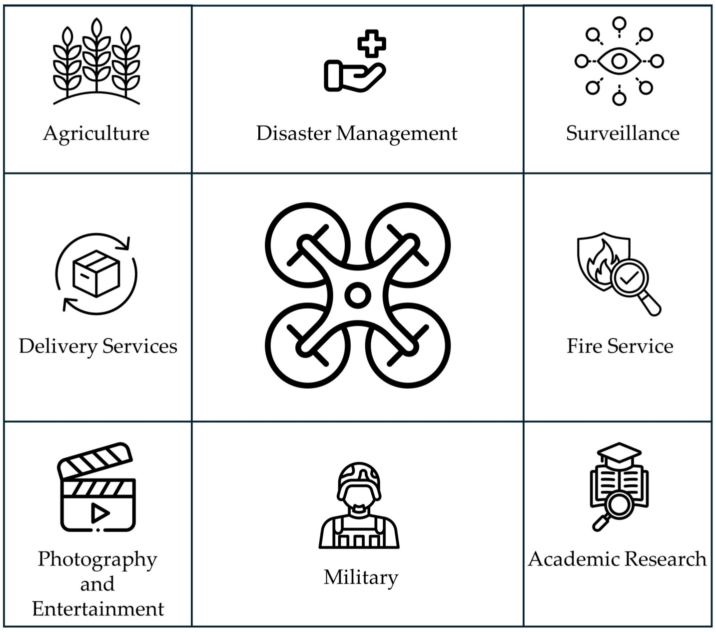

Figure 1. Different quadcopter applications

Although quadcopters have various applications across different fields, this paper focuses specifically on their role in smart agriculture. Given the significant impact quadcopters have on the agrciulture sector, it is crucial to explore their diverse features and capabilities. This paper examines the types of quadcopters used specifically for agricultural missions and discusses the various applications that are uniquely accomplished by quadcopters. Additionally, as the core of the system, quadcopters must be precisely modeled to replicate real-world conditions and achieve the highest possible accuracy. Therefore, this paper explores their modelling in various aspects, such as configurations, reference frames, movements, and mathematical motion equations, to design an efficient model. To the best of our knowledge, this is the only paper in the literature that provides a comprehensive survey of quadcopters in smart agriculture.

The rest of this paper is divided into five sections. Section 2 explores the different types of quadcopters used in smart agriculture. Section 3 discusses the various agricultural missions that quadcopters can perform and provides examples for each application. Section 4 examines quadcopter modelling in terms of configurations and mathematical equations.

Section 5 addresses the challenges faced when using quadcopters in smart agriculture and suggests future directions for overcoming them. Finally, a conclusion section summarizes the main elements of this work.

2. Types of Quadcopters

UAVs come in various types, each designed to fulfill specific missions and meet different operational needs. This section explores the different categories of UAVs, focusing on rotary-wing UAVs, particularly quadcopters. UAVs are divided into five types: blimps, flapping-wing, parafoil-wing, fixed-wing, and rotary-wing. Table 1 presents a comparison among them in terms of structure, advantages, and disadvantages.

Table 1. Different types of UAV.

Type	Structure	Advantages	Disadvantages	References
Blimps	- Spheroid shape - Lifting gas	- High endurance - Most harmless in the case of clashes - Stay airborne even in the case of power failure	- Low speed - Larger in size compared to other UAVs - Lack of maneuverability - Weightless, cannot carry much of a payload	[13,18]
Flapping-wing	- Little wings to fly imitating insects and birds	- Flexible shape	- High energy consumption - Very small	[13,15,18,19]
Parafoil-wing	- One or more propellers at the back for steering control - Parafoil parachute	- Carry larger payload - Benefit from the air power to decrease the energy consumption	- Very sensitive to weather conditions - Non-rigid connection between the parachute's suspension lines and the lift produced complicates control and stabilization	[13,20,21]
Fixed-wing	- Fixed wings - Landing gear - Propeller	- High endurance - High speed - Higher payload limit	-Need a runway to take off and land back -High cost	[13,18,22]
Rotary-wing	- At least one rotor - Propellers - Tail rotor and swashplate in case of helicopter	- Vertical Take-Off and Landing (VTOL) - Ability to hover - High maneuverability - Easy to build - Can be used indoors - Low-cost maintenance	- Low speed - Shorter flight time	[13,15,18,19,23–26]

Among the pre-listed UAV types, blimps, flapping-wing, and parafoil-wing UAVs are rarely used in smart agriculture due to their specific limitations. In contrast, fixed-wing and rotary-wing UAVs are the most commonly selected for various agriculture missions [2]. Deciding between fixed-wing and rotary-wing UAVs depends on the specific mission requirements. For instance, fixed-wing UAVs are preferable for tasks that require longer flight durations and higher speeds, such as aerial mapping and monitoring over large agricultural areas [27,28]. Conversely, rotary-wing UAVs are ideal for missions that require hovering and low-speed operations, such as collecting data from sensor nodes on the ground in crop fields [29,30].

This paper primarily addresses rotary-wing UAVs, specifically quadcopters. These UAVs, characterized by having at least one rotor, are divided into several types, as illustrated in Figure 2. Among these, quadcopters are selected as the core focus of this work. This selection is not random; it is because quadcopters are the most popular UAVs in smart agriculture and are frequently used in research [15–17]. Their superior capabilities and unique features make them the go-to choice for many agricultural applications, outperforming other types of UAVs [31–35].

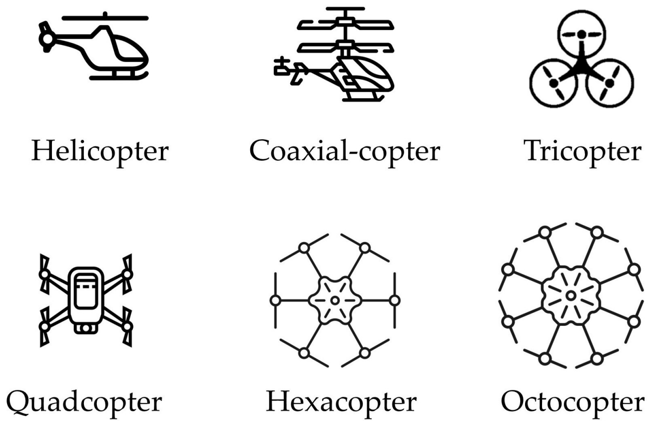

Figure 2. Rotary-wing UAV types.

Theirs characteristics are summarized as follows:

- Quadcopters support heavier payloads by generating a higher lift force through increased thrust from its rotors. The increased lift helps balance the extra weight, allowing quadcopters to stay stable and fly properly while carrying heavier loads;
- Hovering is a key feature that allows quadcopters to maintain a stable position in the air without moving. This capability is achieved when the four rotors generate thrust equal to the gravitational force acting on the quadcopter;
- Quadcopters have a simple body structure, which allows for ease of control and modelling. As a result, users can easily customize and optimize their quadcopters for various applications, enhancing overall performance;
- Quadcopters are easy to assemble. This user-friendly assembly process not only reduces setup time but also allows users to easily upgrade or replace parts, enhancing the quadcopters' adaptability for various applications;
- Quadcopters are defined by their compact design, which not only makes them easy to transport but also enhances their versatility for use in a wide range of environments;
- Quadcopters are simple to control, allowing users to operate them with minimal training, which makes them accessible for a variety of applications;
- Quadcopters possess high maneuverability, enabling them to execute precise movements with ease. This capability arises from their rotors configuration, which allows for the independent control of each rotor's speed and thrust, facilitating navigation through tight and complex spaces;
- Quadcopters do not require runways for operation due to their Vertical Take-Off and Landing (VTOL) capabilities. This feature allows them to ascend and descend vertically, making them suitable for use in a variety of environments;
- Quadcopters are designed for easy pre-flight setup, allowing users to prepare them for flight quickly and efficiently;
- Quadcopters are lower in cost compared to other types of UAVs, making them more accessible to a wider range of users.

After highlighting the features of quadcopters, the next step is to explore the various types utilized in the literature and available in the market to perform agricultural missions.

2.1. Commercial Quadcopters

Drones' global market is continuously increasing year on year, especially in the agriculture sector. Figure 3 shows the agricultural drone global market size, estimated to be 6.11 billion USD in 2024 and forecasted to grow to 17.9 billion USD by 2028 and 23.78 billion USD by 2032 [36,37]. The Compound Annual Growth Rate (CAGR) measures an investment's annual growth rate over a period of time, as defined by (1), and is projected to be 30.8% by 2028 and 18.5% by 2032.

$$\sqrt[P]{\frac{V_f}{V_s}} - 1 \tag{1}$$

where V_f is the final value, V_s is the starting value, and P is the period in years.

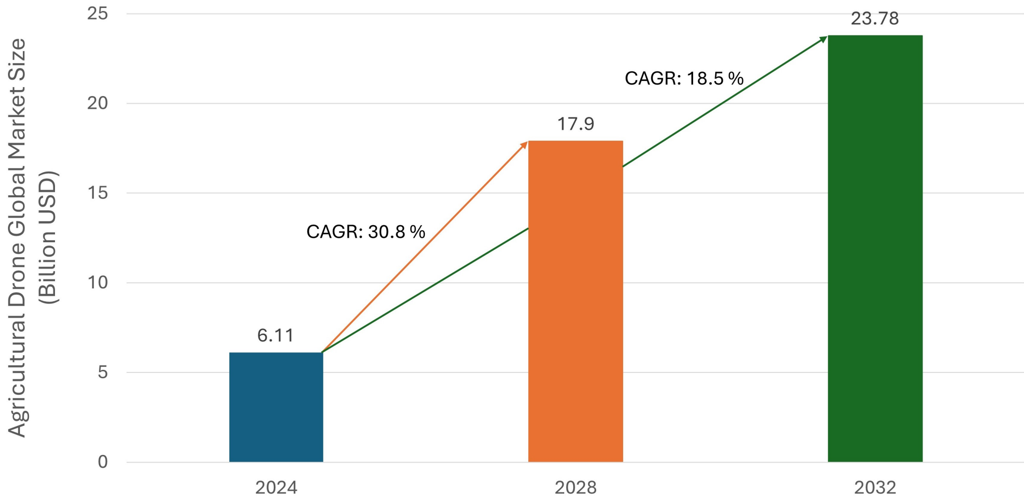

Figure 3. Agricultural drone global market size over the years.

Many commercial drones are available in the market for smart agriculture applications, with rotary-wing drones being the most popular. This subsection specifically explores various types of commercial quadcopters suitable for smart agriculture. A comparison between these quadcopters is presented in Table 2, based on parameters such as weight, battery type, maximum flight time, maximum operating speed, and the equipped camera.

2.1.1. 3DR Iris+

The 3DR Iris+ includes a GoPro camera which allows it to capture high resolution images and videos. Many research papers use this type of drone for different agricultural tasks such as monitoring [38,39], plant health assessment [40,41], and chemical spraying [41]. For example, the authors in [40] used the 3DR Iris+ equipped with a modified Canon S110 camera to capture aerial images of potato crops in Ventaquemada, Boyacá, Colombia. This approach enabled them to assess areas infected by fungus early on, allowing for timely interventions to prevent the spread of diseases and reduce yield losses.

2.1.2. DJI Phantom 3 Standard

The DJI Phantom 3 Standard, illustrated in Figure 4, is equipped with a three-axis gimbal, enabling it to capture stable images and videos. Many research papers have used this drone in different agricultural applications, such as mapping and monitoring [42–46], plant health assessment [47], and in chemical spraying [48]. For example, the authors in [44] used the DJI Phantom 3 equipped with a smart vision system to capture multispectral images in various experimental fields, including an apple orchard, an onion field, and a peach orchard in Idaho, United States. This was carried out to monitor crops and improve production.

Table 2. Specifications of different commercial quadcopters used in smart agriculture.

Type	Weight	Battery	Maximum Flight Time	Maximum Speed	Camera	Release Year	Reference
3DR Iris+	1282 g (including battery)	5100 mAh LiPo 3S	16 min to 22 min	11 m/s	GoPro camera	2014	[49]
DJI Phantom 3 Standard	1216 g (including battery and propellers)	4480 mAh LiPo 4S	25 min	16 m/s	12 MP camera capturing 2.7K videos at 24/25/30 fps	2015	[50]
DJI Matrice 100	2355 g (including TB47D battery) or 2431 g (including TB48D battery)	TB47D 4500 mAh LiPo 6S or TB48D 5700 mAh LiPo 6S	13 min to 40 min	22 m/s	Not applicable	2015	[51]
DJI Inspire 1 Pro	2870 g (including propellers and battery)	4500 mAh LiPo 6S	15 min	18 m/s	16 MP camera capturing 4K videos at 24/25/30 fps	2016	[52]
DJI Phantom 4	1380 g (including battery and propellers)	5350 mAh LiPo 4S	28 min	20 m/s	12.4 MP camera capturing 4K video at 24/25/30 fps	2016	[53]
DJI Matrice 210	3840 g (including two TB50 batteries) or 4570 g (including two TB55 batteries)	Two TB50 4280 mAh LiPo 6S or two TB55 7660 mAh LiPo 6S	13 min to 27 min (with TB50) or 24 min to 38 min (with TB55)	23 m/s	Supports: Zenmuse X4S, Zenmuse X5S, Zenmuse Z30, Zenmuse XT, Zenmuse XT2, SLANTRANGE 3PX, and Sentera AGX710	2017	[54]
DJI Mavic 2 Pro	907 g	3850 mAh LiPo 4S	31 min	20 m/s	20 MP camera capturing 4K videos at 24/25/30 fps	2018	[55]

Figure 4. DJI Phantom 3 Standard (photo by Cam Bradford, sourced from Unsplash under its free license [56]).

2.1.3. DJI Matrice 100

The DJI Matrice 100's maximum flight time depends on its payload, which can reach a maximum of 1 Kg. Many agricultural applications found in the literature were based on the Matrice 100, such as field monitoring and mapping [57–60], and plant health assessment [61,62]. As illustrated in Figure 5, the Matrice 100 was used in a field at Aarhus University, Flakkebjerg, Denmark, to evaluate the crop height and assess its volume for field surveying.

Figure 5. DJI Matrice 100 (used with permission from Christiansen, Martin P. [60]).

2.1.4. DJI Inspire 1 Pro

The DJI Inspire 1 Pro, captured in Figure 6, is equipped with a three-axis gimbal, enabling it to shoot high resolution images and stable videos. It has been featured in some research papers focusing on agricultural applications, such as mapping [63], and irrigation [64,65]. For example, the authors in [64] employed the DJI Inspire 1 Pro to capture images in a maize crop in Hyderabad, India, aiming to identify water-stressed areas. This approach was designed to enhance irrigation practices and improve awareness of crop health.

Figure 6. DJI Inspire 1 Pro (photo by Sam McGhee, sourced from Unsplash under its free license [66]).

2.1.5. DJI Phantom 4

The DJI Phantom 4, shown in Figure 7, includes a three-axis gimbal for stable and high-resolution aerial images ideal for agricultural mapping and monitoring. Additionally, its obstacle avoidance sensor enhances flight safety, reduces crash risks, and supports advanced agricultural applications. The Phantom 4 has been used in numerous research studies to capture high-resolution aerial images for various agricultural applications, including irrigation [67–70], mapping and monitoring [71–75], and plant health assessment [76–80]. For example, the DJI Phantom 4 was used in [71] to capture multi-scale digital elevation models of an agricultural field at the foothills of the Middle Atlas Mountains in Morocco, aiming at managing and monitoring various agricultural parameters.

Figure 7. DJI Phantom 4 (photo by Billy Freeman, sourced from Unsplash under its free license [81]).

2.1.6. DJI Matrice 210

The DJI Matrice 210's maximum flight time depends on its payload, which can reach up to 2.3 kg with TB50 batteries and up to 1.57 kg with TB55 batteries. Additionally, it is equipped with an obstacle sensing system, making it useful for advanced agricultural missions. The use of the Matrice 210 is featured in the literature in various agricultural applications, such as mapping and monitoring [82–84], and plant health assessment [85]. For example, the authors in [83] used the DJI Matrice 210 to capture aerial images of sweet corn fields at the University of Florida's Tropical Research and Education Center in Homestead, Florida, United States. From these images, digital surface and terrain models were generated. Using machine-learning techniques, the authors successfully estimated various crop parameters, such as plant height, biomass, and phenotype, contributing to improved agricultural productivity.

2.1.7. DJI Mavic 2 Pro

The DJI Mavic 2 Pro, shown in Figure 8, has a three-axis gimbal, enabling it to capture stable images and videos. Additionally, it features omnidirectional obstacle sensing which enhances flight safety. The Mavic 2 Pro is found in the literature in many agricultural applications such as monitoring [86–90], plant health assessment [91,92], chemical spraying [93], and irrigation [94]. For example, the authors in [94] employed the DJI Mavic 2 Pro to collect and transport water samples from the Luchenza River in the Traditional Authority of Chimaliro, Thyolo District, Southern Malawi. These samples were tested and analyzed for water quality, aiding in better irrigation practices. The approach proved to be more effective and practical compared to traditional methods.

Figure 8. DJI Mavic 2 Pro (photo by Jacob Buchhave, sourced from Unsplash under its free license [95]).

2.2. Custom-Built Quadcopters

Although commercial quadcopters offer ready-to-use features, custom-built quadcopters offer the chance to build a drone from scratch to meet specific needs and mission requirements. Custom-built quadcopters can be more cost-effective and capable of handling unique tasks that commercial quadcopters may not be able to. Table 3 presents a comprehensive overview of different custom-built quadcopters designed for specific agricultural missions as found in the literature. It showcases their contributions to ameliorating various agriculture practices. In addition, Figure 9 highlights their unique structures designed to meet each agricultural mission's requirements.

Having explored the various types of quadcopters, including commercial and custom-built models, the focus now shifts in the next section to their diverse applications in agriculture, illustrating how these innovative technologies are transforming farming practices and enhancing productivity.

Table 3. Different types of custom-built quadcopters used in smart agriculture.

Quadcopter Description	University or Organization	Year	Agricultural Mission	References
Quadcopter built from Scarab Recon frame	University of Southern Queensland, Toowoomba, Australia	2016	Detecting water in furrow irrigation for better water management in a cotton field	[96]
Agriculture Aid to Seed Cultivation (AASC) quadcopter built with a seed planting unit	Amity University Uttar Pradesh, Noida, India	2016	Planting seeds in uncultivated and inaccessible areas for better field cultivation	[97]
Quadcopter equipped with an Arduino Uno board	BMS College of Engineering, Bengaluru, India	2018	Identifying irrigated areas in a farmland and determining irrigation levels	[98]
Quadcopter with an aluminum metal frame and a spraying mechanism	Vignans Foundation for Science Technology and Research, Guntur, Andhra Pradesh	2019	Designing a quadcopter for semi-autonomous pesticide spraying in smart agriculture	[99]
Quadcopter equipped with a seed canister system	Drone Research Initiative for Environmental Project, Indonesia	2019	Development of a quadcopter for dropping Tamarindus indica seeds for aerial revegetation	[100]
Quadcopter equipped with a seed container and seed-dispersing mechanism	Kumaraguru College of Technology, Coimbatore, India	2020	Designing a quadcopter for seed sowing in forests and roadside areas	[101]
Quadcopter equipped with a smart herbicide sprayer	University of Johannesburg, Johannesburg, South Africa	2021	Detecting weeds in farmland and spraying herbicides based on the weed type	[102]
Two carbon-fiber quadcopters: UAV-L and UAV-R	South China Agricultural University, Guangzhou, China	2022	Quality evaluation of close formation spraying in smart agriculture	[103]
Quadcopter equipped with a pneumatic seed-planting mechanism	University of KwaZulu-Natal Durban, South Africa	2022	Dispensing seedpods at different planting depths and spacing	[104]
Quadcopter with two landing gears and an Orange-Cyan-NearInfrared camera	Universitas Kristen Maranatha Bandung, Indonesia	2023	Capturing aerial images in a rice field and analyzing the obtained data for improved precision agriculture	[105]

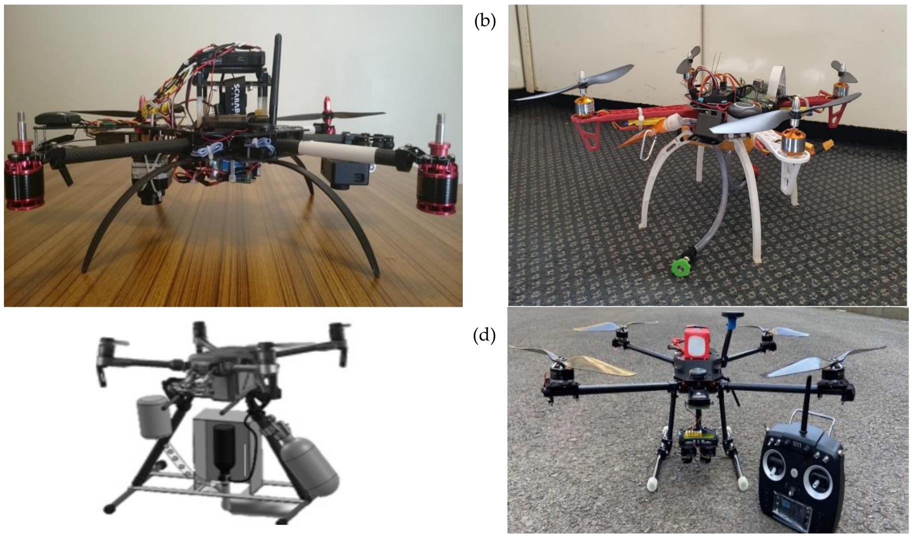

Figure 9. Different custom-built quadcopters used in various agricultural missions: (**a**) furrow irrigation management (Long et al., 2016 [96]); (**b**) weed detection and herbicide spraying (Ukaegbu et al., 2021 [102]); (**c**) pneumatic planting system (Govender et al., 2022 [104]); (**d**) precision agriculture in a rice field (Muliady et al., 2023 [105]).

3. Agricultural Applications of Quadcopters

Quadcopters are being extensively used in smart agriculture, with an essential role in optimizing resources, monitoring large agricultural areas, and ensuring better development throughout the agricultural process.

By integrating quadcopters into each phase of the agricultural cycle, farmers can allocate resources more precisely, detect plant diseases earlier, improve crop yield forecasting, enhance sustainable farming practices, reduce waste, and maximize productivity. With all these countless benefits, quadcopters are becoming an indispensable tool in smart agriculture, achieving significant advancements in the field.

To highlight this significant role, this section examines the various agricultural applications of quadcopters, including chemical spraying, irrigation, crop mapping and monitoring, planting and seeding, and plant health assessment.

3.1. Chemical Spraying

Chemical spraying using quadcopters has been increasingly adopted in smart agriculture by researchers and commercial markets. Being equipped with various sensors, quadcopters can reduce the use of fertilizers and pesticides and increase efficiency.

Two carbon fiber quadcopters were built in [103] to evaluate the spray quality of close formation spraying by applying indoor and outdoor trials in Guangzhou and Changji, China. The two quadcopters were used to collaboratively evaluate the droplet amount, density, and distribution form over different overlapping agricultural areas.

A machine-learning system was applied in [48] with the aid of the commercial quadcopter DJI Phantom 3 Pro, equipped with a 4K camera, to capture images and distinguish between spray and non-spray areas in agricultural croplands and orchards.

The commercial 3DR Iris+ quadcopter was equipped with a Raspberry Pi NoIR camera in [106] to detect areas deficient in chemicals, using image processing, and identify where spraying is needed.

The authors in [99] designed and built a quadcopter for pesticide spraying in agriculture areas in a semi-autonomous way.

3.2. Irrigation

Water distress is one of the major concerns in the agriculture sector. To overcome this problem, quadcopters are used for irrigation purposes to better manage water resources over agricultural fields.

Multispectral images were taken in [107] at an onion field at the United States Department of Agriculture (USDA) with the aid of a Hover quadcopter to recognize irrigation non-uniformity for better management. In addition, the same quadcopter was used to assess irrigation levels using aerial images of pomegranate field in USDA [108].

The authors in [98] designed a quadcopter to assess if a part of a farmland is irrigated or not using image processing. A quadcopter was built in [109] to take aerial thermal images, identify dry patches using image processing, and then activate specific smart sprinklers placed in the farmland based on the obtained data and other parameters such as weather conditions. The authors in [96] designed a quadcopter to detect water in irrigation furrows for better water management in a cotton field in Yargullen, Queensland.

A commercial DJI Inspire-1 Pro quadcopter was used in [64] to identify water-stressed areas in maize fields in Hyderabad, India.

The DJI Phantom 4 Pro was used in [67] to map irrigated agricultural areas in Limpopo Province, South Africa, in [68] to capture aerial images of rice fields and estimate their growth for better irrigation management, in [69] to provide high spatial images of cotton field in Texas High Plains for better irrigation management, and in [70] to take aerial images of sugarcane fields in Nanning, China and estimate irrigation levels.

3.3. Crop Mapping and Monitoring

The use of quadcopters in agriculture mapping plays a significant role in helping farmers make more informed decisions and achieve more development in the farming sector.

The authors in [60] equipped a DJI Matrice 100 quadcopter with a Light Detection and Ranging (LiDAR) sensor to observe crop fields and evaluate their production and environmental parameters.

The commercial DJI Matrice 210 was used in [84] with image processing techniques to map and monitor crop fields in Northern Italy for better precision agriculture.

A Pelican quadcopter captured multispectral images in [110] to extract agricultural features on the field and evaluate vegetation status.

The DJI Inspire was used in [63] to take high-resolution images of crop fields and proved to be more effective than using conventional ground-observer methods.

A combination of DJI Phantom 4 with an Unmanned Ground Vehicle (UGV) was proposed in [75] to provide 3D mapping of orchard fields. Additonally, the DJI Mavic Pro was employed with UGV in crop fields in Eschikon, Switzerland for precision agriculture [111].

The authors in [29,30] used a quadcopter in a WSN-based application to improve crop field management by nominating cluster heads among ground sensors to organize data collection, gathering information from the selected cluster heads, and localizing ground sensors.

3.4. Planting and Seeding

Quadcopters also play a significant role in planting, surpassing traditional agricultural methods. This modern utilization offers precision and efficiency in seed dispersal, allowing for the optimal use of resources.

A quadcopter was built in [101] with an appropriate mechanism to sow seeds in forests and roadside areas. A quadcopter was designed in [100] to disperse seeds for the specific tree species “Tamarindus Indica” in revegetation fields in West Java. The authors in [104] demonstrated how the use of a quadcopter in farm seeding can assist land machinery in sowing procedures or even surpass them. The study presented a quadcopter equipped with a pneumatic system to dispense seeds at specific planting depths, making it suitable for low-cost farming applications. A quadcopter was built in [97] to plant seeds in inaccessible agriculture areas for better cultivation.

The authors in [112] used a GMH-3 quadcopter to optimize a rice-seeding spreader for better uniformity in distribution.

3.5. Plant Health Assessment

By offering a bird's eye view, quadcopters can provide detailed images and information on plant health. This enables the early detection of diseases, pests, and nutrient deficiencies, leading to healthier plants and better agricultural productivity.

Various quadcopters were used to execute plant health assessment in many research works, as follows:

- DJI Phantom 4:
  - It was used in [76] to take multispectral images and assess the health status of olive trees by evaluating different parameters such as nutritional values, biometric features, and vegetative status.
  - It was employed in [77] to assess soil health by counting rice plants in an agricultural area in Tando Adam, Sindh, Pakistan.
  - It was selected in [78] to capture multispectral images and identify banana areas infected with Panama disease, specifically "Fusarium wilt". This monitoring enables early treatment and improvements in planting methods.
  - Its Pro version was implemented in [79] to capture high-resolution images to monitor the health of Eucalyptus pellita, detecting any infestations from pests and viruses.
  - The authors in [80] used it to demonstrate that aerial images can serve as a cost-effective alternative to traditional field measurements for assessing citrus diseases such as Huanglongbing and Phytophthora, leading to improved crop production management.
- Co-Axial Quadcopter: it was implemeted in [113] to show how multispectral images can assist satellite data in detecting stress in trees and monitoring forest health.
- DJI Matrice 100: it was paired in [62] with a camera to capture multi-band images for detecting orchard apple trees and evaluating vegetation parameters for better health assessment.
- DJI Inspire 2: it was selected in [114] to evaluate plant vegetation and rice crop damage, resulting in improved crop monitoring.
- DJI Phantom 3 Standard: two of these drones were used in [115] to take multispectral images to assess the health of Capsicum annuum crops for better field productivity.
- UX4: it was implemeted in [116] to capture hyperspectral images to identify trees affected by citrus gummosis, the predominant fungal disease in Brazil, facilitating more effective management of plant health.

After exploring the various quadcopters employed in different agricultural missions, we selected several examples and presented them in Table A1, given in Appendix A, where we highlight the limitations identified in each study. After evaluating the challenges faced, we proposed specific recommendations, such as employing more advanced techniques to address and overcome these issues. These suggestions can open the door for future work and provide a basis for future advancements in the field.

Having established a comprehensive understanding of the diverse applications of quadcopters in agriculture, the discussion now transitions to quadcopters' modelling in the next section, examining various aspects essential for ensuring a reliable design.

4. Modelling of Quadcopters

Modelling quadcopters is a crucial aspect of designing them effectively. The better the quadcopter model is, the closer it will be to its real-world implementation. Therefore, it is essential to explore quadcopters' configurations, aspects, and their mathematical motion equations.

4.1. Configurations

Quadcopters have four rotors, "1, 2, 3, 4", positioned relative to the body coordinate system based on two configurations: the "Plus, +" and the "Cross, x" configurations, as illustrated in Figure 10.

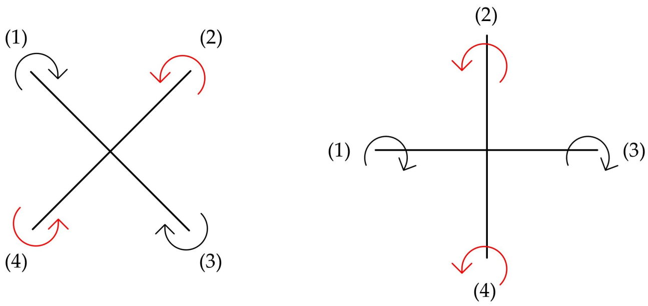

Figure 10. Cross and plus configurations.

The cross configuration is more commonly used in both the literature and the market than the plus configuration because it is more stable. Additionally, users can slightly adjust the speed of each propeller rather than only varying the speeds of two propellers [15,117]. In cross configurations, the pair of diagonal rotors 1 and 3 rotate clockwise, and the opposite pair rotate counter-clockwise.

4.2. Reference Frames

Quadcopters are characterized by two reference frames: the inertial or earth frame (E-frame) and the body frame (B-frame), as shown in Figure 11.

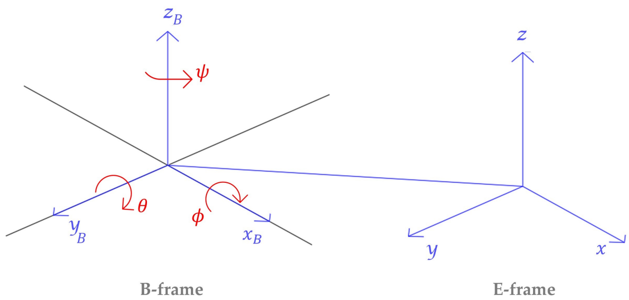

Figure 11. Quadcopter reference frames.

They are described by their six Degrees of Freedom (6DOF), which include their linear positions measured in meters (m) and angular positions measured in radians (rad), known as attitude. Their linear and angular positions are defined in the E-frame, and their translational and rotational velocities are defined in the B-frame, as shown in Table 4.

Table 4. Linear and angular terms in reference frames.

Reference Frames	Linear	Angular
E-frame positions	x (forward/backward)	ϕ (roll)
	y (left/right motion)	θ (pitch)
	z (up/down)	ψ (yaw)
B-frame velocities	u	p
	v	q
	w	r

With four rotors controlling 6DOF, quadcopters are considered highly under-actuated non-linear models.

4.3. Movements

Quadcopters can reach specific locations and modify their height and attitude based on four basic movements in the cross configuration, shown in Figure 10:

- Thrust: this movement occurs when all the rotor speeds are decreased or increased by the same value, causing the quadcopter to raise or lower its altitude;
- Roll: This movement occurs when increasing the speed of rotor 1 and decreasing the speed of rotor 3 or vice versa, while keeping rotors 2 and 4 at the same speeds. This creates a torque around the x-axis with respect to the B-frame, as shown in Figure 11, causing the quadcopter to roll;
- Pitch: This movement occurs when increasing the speed of rotor 4 and decreasing the speed of rotor 2 or vice versa, while keeping rotors 1 and 3 at the same speeds. This generates a torque around the y-axis with respect to the B-frame, as shown in Figure 11, causing the quadcopter to pitch;
- Yaw: This movement occurs by increasing the speed of rotors 2 and 4 and decreasing the speed of rotors 1 and 3 or vice versa. This creates a torque around the z-axis with respect to the B-frame, as shown in Figure 11, causing the quadcopter to yaw.

4.4. Universal Assumptions

Many universal assumptions are used in the literature [118–124], before deriving the quadcopter's model equations to simplify its nonlinearities and address mathematical complexities while keeping the model as accurate as possible. Most of these assumptions are summarized as follows:

- The quadcopter's body structure is considered rigid;
- The quadcopter's body frame is symmetric, leading to a diagonal inertia matrix;
- The drag and thrust factors are proportional to the square of the rotors' speeds;
- The center of gravity and the quadcopter's body mass are considered unified. However, this assumption might be affected by the load distribution on the quadcopter; therefore, the load should be distributed symmetrically;
- The quadcopter's principal body axes and body frame are aligned.

4.5. Motion Equations

Two techniques can be used to derive the motion equations of quadcopters: the Newton–Euler technique or the first principle of approximation. The first technique is based on the Newton–Euler and Euler–Lagrange methods, while the second technique relies on quaternion and superposition approaches. Many methods, such as angular orientation, voltage-based techniques, and force-moment, are based on the Newton–Euler technique, since it is widely used and more preferred and efficient than the first principle of approximation [117,125]. Therefore, the mathematical motion equations presented in this work are based on the Newton–Euler technique, specifically on the angular orientation approach.

4.5.1. Kinematics

The 6DOF quadcopter is presented by the kinematics equations defined in (2) and (3) [120,126–130].

$$L_V = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = R \begin{bmatrix} u \\ v \\ w \end{bmatrix} \tag{2}$$

$$A_V = \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = T \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{3}$$

where L_V is the linear velocity vector in (m/s) in E-frame and A_V is the angular velocity vector in (rad/s) in E-frame. T and R are the transfer and rotation matrices, respectively, between both frames and are given in (4) and (5).

$$T = \begin{bmatrix} 1 & \sin(\phi)\tan(\theta) & \cos(\phi)\tan(\theta) \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \frac{\sin(\phi)}{\cos(\theta)} & \frac{\cos(\phi)}{\cos(\theta)} \end{bmatrix} \quad (4)$$

$$R = \begin{bmatrix} \cos(\psi)\cos(\theta) & -\sin(\psi)\cos(\phi) + \cos(\psi)\sin(\theta)\sin(\phi) & \sin(\psi)\sin(\phi) + \cos(\psi)\sin(\theta)\cos(\phi) \\ \sin(\psi)\cos(\theta) & \cos(\psi)\cos(\phi) + \sin(\psi)\sin(\theta)\sin(\phi) & -\cos(\psi)\sin(\phi) + \sin(\psi)\sin(\theta)\cos(\phi) \\ -\sin(\theta) & \cos(\theta)\sin(\phi) & \cos(\theta)\cos(\phi) \end{bmatrix} \quad (5)$$

These kinematics equations are a combination of translational and rotational movements. The translational terms are related to the quadcopter's position, while the rotational terms are related to its orientation.

For translational movements, the quadcopter's linear velocities are defined in the B-frame, while its linear positions are defined in the E-frame, as given in Table 4. Therefore, the rotation matrix R is used for transforming the linear terms between these two reference frames, as provided in (2).

For rotational movements, the quadcopter's angular velocities are defined in the B-frame, while its angular positions are defined in the E-frame, as given in Table 4. Therefore, the transfer matrix T is used for determining the relationship between the rate of change in the Euler angles and the angular velocities in the B-frame, as provided in (3).

4.5.2. Dynamics

The quadcopter's motion is described by the dynamics equation defined in (6), which is generic and can be used for any rigid body [120,126,127,129–133].

$$M_B\dot{v} + C_B(v)v = \Lambda \quad (6)$$

where M_B is the system's inertia matrix given in (7), $C_B(v)$ is the Coriolis Centripetal matrix given in (8), v is the generalized velocity vector given in (9) and containing the linear and angular velocities in (m/s) and (rad/s), respectively, $\dot{v}$ is the generalized acceleration vector containing the linear and angular accelerations in (m/s^2) and (rad/s^2), respectively, and Λ is the vector containing the force and torque terms in (N) and (Nm), respectively.

$$M_B = \begin{bmatrix} m & 0 & 0 & 0 & 0 & 0 \\ 0 & m & 0 & 0 & 0 & 0 \\ 0 & 0 & m & 0 & 0 & 0 \\ 0 & 0 & 0 & I_{xx} & 0 & 0 \\ 0 & 0 & 0 & 0 & I_{yy} & 0 \\ 0 & 0 & 0 & 0 & 0 & I_{zz} \end{bmatrix} \quad (7)$$

$$C_B(v) = \begin{bmatrix} 0 & 0 & 0 & 0 & mw & -mv \\ 0 & 0 & 0 & -mw & 0 & mu \\ 0 & 0 & 0 & mv & -mu & 0 \\ 0 & 0 & 0 & 0 & I_{zz}r & -I_{yy}q \\ 0 & 0 & 0 & -I_{zz}r & 0 & I_{xx}p \\ 0 & 0 & 0 & I_{yy}q & -I_{xx}p & 0 \end{bmatrix} \quad (8)$$

$$v = \begin{bmatrix} u & v & w & p & q & r \end{bmatrix}^T \quad (9)$$

where m is the body mass in (kg) and "I_{xx}, I_{yy}, I_{zz}" are the diagonal terms of the inertia matrix in (Nms^2).

As shown in (7), the inertia matrix is diagonal and constant, following the universal assumptions adopted in this approach to simplify the mathematical complexity. The dynamics equation in (6) is generic and can be applied to any quadcopter, based on the previously discussed assumptions. The vector Λ contains the specific forces and torques that must be incorporated into the model depending on the type of quadcopter and the mission requirements. By choosing a generic model, we provide a flexible framework that researchers can build upon and customize for various applications.

4.5.3. Aerodynamics

The force and torque vector Λ can include different components depending on the aerodynamics effects considered in each work. Based on many research papers, these aerodynamics components can be summarized as follows:

- Gravitational force: it affects only the linear terms and is determined by the acceleration of the quadcopter due to gravity [117,120,126,127,129–142];
- Gyroscopic torque: it affects only the angular terms and can be generated when the roll or pitch values are non-zero. Additionally, it is produced when the propellers rotate, with one pair rotating clockwise and the other pair rotating counterclockwise. Consequently, if the total speed of propellers is non-zero, an imbalance will occur [120,126,127,129,131–135,138,142,143];
- Forces and torques: they are generated by the quadcopter's movements, as mentioned in Section 4.3, where drag and thrust factors are also included in their corresponding equations. Additionally, quadcopters may face different external disturbances, such as wind, which can cause a blade-flapping effect that affects the motor force equations. This flapping effect can be categorized into two types: low-amplitude, known as Vortex Ring State (VRS), and high-amplitude, known as Turbulence Wake State (TWS). These fluctuations can be attenuated by increasing the quadcopter's horizontal speed [31,32,117,120,126,129–136,138,139,142,143].

After discussing quadcopters' modelling in all its aspects, attention now shifts to the challenges faced in their deployment and the future directions that could enhance their impact in agricultural practices.

5. Challenges and Future Directions

The use of quadcopters in smart agriculture presents various benefits but also brings significant challenges that need to be addressed. This section discusses these challenges and outlines future directions for more effective implementation.

5.1. Consumption of Resources

5.1.1. Challenges

One of the major challenges of using quadcopters in smart agriculture is their limited flight duration and battery life. Most quadcopters have a maximum flight time of 15 to 40 min, which poses significant challenges, especially for large-scale agricultural areas where vast fields need to be covered in a single mission. Additionally, it can be difficult to balance the diverse requirements of agricultural missions with the need to optimize resources simultaneously [144–146].

5.1.2. Future Directions

Future research could focus on developing advanced battery technology that can be mounted on quadcopters or using renewable energy sources, such as solar power, to prolong flight duration [147]. However, in the case of integrating solar cells, they should be lightweight and positioned properly to avoid negatively impacting the quadcopter's weight or functionality. For example, the authors in [148] proposed an efficient solar-powered quadcopter system, incorporating a small battery, which extended the quadcopter's endurance by 48.7 times compared to using the battery alone. This innovative design did not compromise the quadcopter's functionality, demonstrating its potential for extended missions in agriculture. Such technology is ideal for long-duration tasks like mapping vast areas or collecting data from large fields in a significantly reduced time.

Alternatively, users could consider solar charging stations where quadcopters can stop, recharge, and resume operations. For example, the authors in [149] proposed a design for solar-powered mobile charging stations equipped with a battery selection system to control the charging process and optimize battery replacement. In this system, quadcopters can autonomously land, swap their batteries, and quickly resume their missions. This approach has significant potential in agriclutral applications, where charging stations can be placed across large fields. This is particularly valuable for missions such as the precision mapping of large farms, the real-time monitoring of crop health, and managing irrigation.

Additionally, path optimization algorithms can be used to accomplish the quadcopter's mission in less time and with lower energy consumption [150]. For example, the authors in [151] conducted a study using a quadcopter to identify stressed regions in a field. An optimal path for spraying was then determined using a specific path optimization algorithm. This approach helps manage irrigation by ensuring efficient spraying in less time, and it can also be applied to other tasks such as chemical spraying, crop monitoring, and planting.

Furthermore, multiple UAVs can collaborate to perform the same agricultural tasks more quickly and efficiently [152]. For example, the authors in [153] demonstrated that a swarm of UAVs is more efficient than a single UAV for mapping large agricultural fields. The UAVs, each equipped with different sensors, coordinated to map large areas in parallel. This approach illustrates how multiple UAVs can rapidly cover vast fields, and can be similarly applied to other agricultural tasks.

5.2. Data Processing

5.2.1. Challenges

Agricultural quadcopters are equipped with various sensors that generate a massive amount of data, such as high-resolution aerial images, data collected from ground sensors, multispectral data, and more. This data must then be analyzed and interpreted to provide feedback and enable proactive actions. However, processing large amounts of data is very challenging, especially in real-time, due to computational challenges and data instability [154–156].

5.2.2. Future Directions

Future directions could include advanced techniques and software platforms, such as those based on AI and cloud-computing technologies, that can handle and process large datasets effectively and improve decision-making [157,158]. For instance, the authors in [159] demonstrated that combining cloud-, fog-, and edge computing can enhance data handling in UAV-based applications for smart agriculture. This combination can improve real-time decision-making, increase the accuracy of data analysis, and optimize agricultural tasks such as irrigation management, field mapping, and plant health monitoring.

5.3. Environmental Factors and Dynamic Obstacles

5.3.1. Challenges

Quadcopters are affected by adverse weather conditions, such as rain, wind, and clouds, which can reduce their reliability in certain climates. Additionally, dense vegetation and dynamic obstacles can impact the safety of quadcopters and increase the risk of crashes [160–162].

5.3.2. Future Directions

Future research could explore advanced control techniques to adapt to environmental factors and dynamic obstacles [163]. Additionally, the use of AI, advanced navigation systems, and modern obstacle detection sensors could make quadcopters more robust and more effective in collision avoidance [164,165]. For example, the authors in [166] developed a data-driven dynamic obstacle avoidance system for a quadcopter equipped with a liquid tank for pesticide spraying. The system uses data from one long-range wide-angle sensor and four single-point detection sensors to accurately detect and avoid obstacles. By processing sensor data in real-time, the quadcopter achieves precise obstacle avoidance, while maximizing spray coverage and minimizing mission time. This technology allows UAVs to perform agricultural missions efficiently while eliminating concerns about potential damage from collisions.

5.4. Security Threats

5.4.1. Challenges

Quadcopters can face several security threats, such as unauthorized control, mission disruption, the alteration of flight paths, the exposure of important agricultural data, the disruption of communication and data transmission between quadcopters and ground sensors, and misuse for unauthorized purposes [167–170].

5.4.2. Future Directions

Future directions could focus on implementing enhanced cybersecurity measures, such as stronger encryption and authentication protocols, and integrating AI techniques to detect and respond to unusual behavior [170,171]. These countermeasures would improve system integrity and reduce security risks. For instance, the authors in [172] proposed a hybrid machine-learning technique combining logistic regression and random forest algorithms to detect attacks on a quadcopter network. By utilizing machine learning, this approach enhances the security of an IoT-enabled drone, reducing cybersecurity threats and ensuring robust protection. This is particularly beneficial for agricultural missions, such as precision farming and crop monitoring, where sensitive data regarding crop yields must be protected against potential cyber attacks. For example, unauthorized access to these data could lead to significant financial losses or the misuse of information by competitors, underscoring the necessity for robust cybersecurity measures in UAV-based operations within smart agriculture.

6. Conclusions

In this paper, a comprehensive survey was conducted on the use of quadcopters in smart agriculture. Among all UAV types, quadcopters were selected due to their multiple features and capabilities, such as flexibility, low cost, ease of use, high maneuverability, ability to hover, and many more cited advantages.

An examination of the types of quadcopters specifically used in smart agriculture was carried out, categorizing them into two groups: commercial and custom-built quadcopters. Each type was described with its relevant specifications, and examples were provided for each, showcasing their wide applicability in smart agriculture across different countries.

Subsequently, a discussion was presented on the various applications that quadcopters can perform in this field, such as planting, irrigation, mapping, and monitoring. This analysis demonstrated how quadcopters are essential tools in every phase of the agricultural cycle. Additionally, we carefully presented in Table A1 key examples along with their limitations, highlighting the significance of these findings and offering valuable suggestions for future advancements in the field.

Furthermore, the modelling of quadcopters was explored in detail, covering aspects from configurations to deriving mathematical equations. Kinematics, dynamics, and aerodynamics equations were provided to describe the motion and behavior of quadcopters.

Finally, the challenges encountered in this field were identified, along with proactive measures and future directions proposed for continuous improvement.

To sum up, although the use of UAVs in smart agriculture has been discussed in other works, to the best of our knowledge, none have particularly explored the most popular among them, "quadcopters", and their particular use in smart agriculture. Therefore, this paper provides researchers and innovators working with quadcopters in smart agriculture with a deep dive into the different aspects of these UAVs, including types, applications, and modelling techniques, paving the way for future advancements in the rapidly growing field of smart agriculture.

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Appendix A

Table A1. Examples of quadcopters used in agriculture, with limitations and proposed solutions.

Objective	Agricultural Mission	Limitations	Suggestions	Reference
Development of a high-accuracy machine-learning system with high computational speed for distinguishing between spray and non-spray areas in UAV-based spraying applications	Chemical spraying	The proposed machine learning system had limitations in identifying sprayed and non-sprayed areas in the complex canopies of crop fields.	• Utilize more advanced algorithms, such as convolutional neural networks; • Combine data from different advanced sensors, such as LiDAR or ground sensors, to provide the UAV with additional data; • Expand the training data to include various types of complex canopies.	[48]
Development of an automated machine vision algorithm for processing thermal imagery captured by UAV over a cotton field to monitor the progress of furrow irrigation across large field areas	Irrigation	False-positive readings in darkened areas of the image, a lower accuracy of water detection in images taken at higher altitudes, and camera performance affected by wind.	• Utilize advanced image processing algorithms; for example, those based on deep learning; • Employ a higher-resolution camera mounted on a gimbal for higher stabilization in case of wind; • Optimize flight altitude, ensuring improved image resolution.	[96]
Creating regional-scale crop maps by utilizing both satellite and UAV-based ground truth data	Crop mapping and monitoring	Limited site selection where UAV may have difficulty flying at certain elevations and slope, lower accuracy in intercropping or mixed lands, and limited training data size	• Utilize more advanced UAVs with advanced control techniques capable of operating in more challenging terrain; • Increase the training data size by collecting images across different challenging crop types; • Employ advanced algorithms such as deep-learning models	[63]
Designing a seed-sowing UAV system with payload calculation for tree planting	Planting and seeding	Reliable communication is needed to ensure a continuous link between the UAV and ground station. Static waypoints are adopted, which can cause the system to be affected by dynamic conditions. Environmental challenges, such as obstacles or weather conditions, may also impact the UAV.	• Employ more robust communication techniques to ensure a stable connection; • Use reliable GPS technologies such as real-time kinematic (RTK) GPS for precise operations; • Implement dynamic waypoint generation to adapt to any changes; • Employ advanced control systems for navigation as well as advanced path planning and collision avoidance techniques based on machine learning.	[101]

Table A1. Cont.

Objective	Agricultural Mission	Limitations	Suggestions	Reference
Detecting pests and diseases through images of canopy foliage captured by UAV for early health monitoring of Eucalyptus pellita plantation	Plant health assessment	The 30 min UAV flight duration used in this study may limit its applicability to larger field areas. Also, the proposed algorithm was not reliable for detecting trees with smaller crown sizes and faced difficulties in densely planted areas.	• Utilize a swarm of UAVs to execute the same mission over larger crop areas; • Enhance the algorithm to not be affected by crown size by relying on advanced detection sensors; • Implement machine-learning algorithms that can address the issue of overlapping crowns.	[79]

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