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# Comprehensive Review of Agriculture Spraying UAVs Challenges and Advances: Modelling and Control

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## Keywords

Agriculture, Control, Drone, Mapping, Sensing, Model, Pesticide, Spray, UAV

**Abstract**

The integration of Unmanned Aerial Vehicles (UAVs) into agriculture has emerged as a transformative approach to enhance resource efficiency and enable precision farming. UAVs are used for various agricultural tasks, including monitoring, mapping, and spraying of pesticides, providing detailed data that support targeted and sustainable practices. However, effective deployment of UAVs in these applications faces complex control challenges. This paper presents a comprehensive review of UAVs in agricultural applications, highlighting the sophisticated control strategies required to address these challenges. Key obstacles, such as modelling inaccuracies, unstable centre of gravity (COG), due to shifting payloads, fluid sloshing within pesticide tanks, and external disturbances like wind, are identified and analysed. The review delves into advanced control methodologies, with particular focus on adaptive algorithms, backstepping control, and machine learning-enhanced systems, which collectively enhance UAV stability and responsiveness in dynamic agricultural environments. Through an in-depth examination of flight dynamics, stability control, and payload adaptability, this paper highlights how UAVs can achieve precise and reliable operation despite environmental and operational complexities. The insights drawn from this review underscore the importance of integrating adaptive control frameworks and real-time sensor data processing, enabling UAVs to autonomously adjust to changing conditions and ensuring optimal performance in agriculture. Future research directions are proposed, advocating for the development of control systems that enhance UAV resilience, accuracy, and sustainability. By addressing these control challenges, UAVs have the potential to significantly advance precision agriculture, offering practical and environmental benefits crucial to sustaining global food production demands.



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# Nomenclature

| | |
|---|---|
| UAV | Unmanned Aerial Vehicle |
| PID | Proportional-Integral-Derivative |
| IBS | Integrator Backstepping |
| IBKS | Incremental Backstepping |
| SOGP | Sparse Online Gaussian Process |
| 6DoF | 6-degree-of-freedom |
| GM | Gain margin |
| PM | Phase margin |
| INDI | Incremental Dynamic Inversion |
| CLF | control Lyapunov function |
| GP | Gaussian Processes |
| CoG | Centre of Gravity |

# 1 Introduction

According to research by the International Telecommunication Union (ITU) and the Food and Agriculture Organisation of the United Nations (FAO), it is projected that the global population will reach 9.7 billion by 2050. To meet this growing demand, global food production must increase by approximately 70% in the coming decades [1]. However, the agriculture sector faces significant challenges, including limited arable land, resource constraints, and environmental concerns. Increasing the efficiency of agricultural operations through the adoption of smart technologies is essential to address these challenges [2].

Among these technologies, Unmanned Aerial Vehicles (UAVs) have emerged as a promising tool for enhancing agricultural productivity. UAVs offer several advantages over traditional methods, including the ability to collect detailed data, perform precision tasks, and operate in challenging environments. Their applications in agriculture range from mapping and monitoring to targeted spraying, enabling farmers to make data-driven decisions and optimise resource use [3]. Beyond agriculture, UAVs have also been widely used in areas such as disaster management [4], aerial inspections [5], logistics [6], and surveillance [7].

Unmanned helicopters have been utilised in agriculture since the 1980s, with Yamaha's R-50 (1990) and later the R-MAX being early examples, capable of crop spraying with a 20 kg payload [8]. Although EU regulations restrict drone spraying [9], UAVs offer advantages such as access to difficult terrain and minimising crop damage. In precision agriculture, helicopter and multirotor UAVs enable low-speed or stationary flight, facilitating detailed diagnostics and sensor-based sampling. Popular models like the DJI Agras T50 achieve high efficiency, spraying up to 21 ha/h at 15 $dm^3$/ha [10], enhancing operational savings and time efficiency.

One of the key advantages of UAVs is their ability to provide high-resolution data at a lower cost compared to traditional methods such as satellites or manned aircraft [11]. For example, UAVs equipped with advanced sensors can assess crop health by measuring light absorption to determine chlorophyll levels in leaves [12]. In addition, UAVs enable precision agriculture practices, such as the application of targeted herbicides or pesticides, which reduce chemical usage and environmental impact compared to conventional blanket spraying methods [13].

The use of UAVs in agriculture continues to evolve, and ongoing research continues to expand their capabilities. Current applications include tree canopy estimation using LiDAR (Light Detection and Ranging) systems [14], SLAM (Simultaneous Location and Mapping) for navigation [15], and precision spraying for pest control [16]. Among these, rotorcraft UAVs are particularly popular due to their ability to hover and perform agile manoeuvres, making them well-suited for a wide range of agricultural tasks.

However, the effective implementation of UAVs in agriculture is not without challenges. One of the most demanding applications is agricultural spraying, which introduces unique control challenges due to the dynamic nature of liquid payloads. Factors such as liquid sloshing, changes in the centre of gravity (CoG), and external disturbances such as wind can significantly affect the stability and performance of spraying UAVs. These challenges require advanced control strategies to ensure precise and efficient operation.

This paper provides a comprehensive review of the role of UAVs in agriculture, with a focus on the control challenges associated with agricultural spraying. Section 2 explores the structures of UAVs through their applications in agriculture. Section 3 investigates the applications of UAVs in agriculture, including mapping, monitoring, and spraying. Section 4 examines the key control challenges specific to spraying UAVs, such as liquid tank modelling, CoG variations, and wind disturbances. Section 5 reviews the control methodologies proposed in the literature to address these challenges. Finally, the paper concludes with a discussion of future research directions and opportunities in this field.

# 2 UAV Structures for Agricultural Applications

The structural configurations of UAVs used in agriculture vary widely depending on the specific tasks they are designed to perform [17]. Agricultural UAVs are generally categorised into fixed-wing, multi-rotor, and hybrid structures, each offering unique advantages suited to different agricultural applications.

**Fixed-Wing UAVs** are typically preferred for large-scale mapping and monitoring due to their extended flight endurance and ability to cover expansive areas efficiently [18]. With a longer battery life and greater flight range, fixed-wing UAVs are ideal for capturing high-resolution aerial images over large crop fields or surveying vast agricultural landscapes in a single flight [19]. However, these UAVs require more space for take-off and landing, which can limit their usage in confined or obstructed environments such as dense orchards or irregularly shaped fields [20].

**Multi-rotor UAVs**, such as quad-copters and hexa-copters, are commonly used in precision agriculture for tasks requiring precision and manoeuvrability, such as crop spraying, targeted weed control, and close-range inspections [21]. These UAVs are capable of hovering and operating at low altitudes, allowing accurate and uniform spraying applications, as well as detailed crop health assessments. Multi-rotor UAVs offer enhanced stability and agility in tight spaces, making them suitable for use in orchards and densely planted areas. However, their flight endurance and range are generally limited by battery capacity, restricting their application in large-scale agricultural monitoring without frequent recharging [22].

**Hybrid UAVs** combine the capabilities of fixed-wing and multi-rotor designs, enabling both vertical take-off and efficient forward flight [23]. These UAVs offer the advantage of greater endurance for greater coverage, while retaining the vertical take-off capabilities necessary in confined

areas [24]. Hybrid UAVs are increasingly being used in precision agriculture for tasks that benefit from hovering and range capabilities, such as spraying and monitoring of a wide area in mixed terrain [25]. Despite their versatility, hybrid UAVs tend to have complex structural and control systems, which can increase costs and maintenance requirements [26].

Each UAV structure presents unique advantages and limitations in agricultural settings. Fixed-wing UAVs provide extensive coverage, multi rotor UAVs allow for precision in confined areas, and hybrid designs offer a balanced approach. The selection of the UAV structure depends on the specific agricultural application, as well as operational considerations such as field size, terrain type, and desired data precision and detail level. With advances in UAV technology, these structures are increasingly optimised for agricultural tasks, improving data acquisition, efficiency, and the effectiveness of precision farming practices[27].

# 3 Applications with UAVs in Agriculture

Unmanned Aerial Vehicles (UAVs) have become an integral part of precision agriculture, offering innovative solutions to monitor crop health, apply fertilisers and pesticides, and collect valuable data for informed decision-making [29]. UAVs provide significant advantages over traditional methods, such as overcoming crop height limits, reducing soil compaction, and enabling the precise application of agricultural inputs [30].

Unmanned aerial systems (UAVs) are widely used in remote sensing applications for precision farming [31]. Using drones equipped with different types of sensors, UAVs can be used to determine which areas of the crop need different management [32]. This gives farmers the ability to detect and react in a timely manner to any problem [33]. Such as health monitoring and disease detection, growth monitoring and yield estimation, weed management and detection, etc. UAVs can be used in many different applications in precision agriculture [34]. Due to the frequent use of UAV applications in UAV applications, it has become an area of interest and is considered the future of remote sensing [35].

Pests, weeds, and diseases in plants seriously impact agricultural production and food security worldwide [36]. Approximately 30% of the crop loss, in general, is due to these threats annually [37]. The problem is more important with the consideration of population growth, resource shortages, environmental problems, and climate changes [38]. Therefore, an advanced plant protection system to prevent and control plant diseases and pests is of paramount importance for sustainable agricultural productivity and effective adoption.

On the other hand, since agriculture and farming are related in many different fields, various studies related to agriculture have been made. Such as; identifying the target environment [39], poultry production [40], disinfectant spraying against Covid-19 [41], etc.

Despite these benefits, the effective implementation of UAVs in agriculture depends on addressing various control challenges [42, 43, 44]. These challenges include modelling errors, external disturbances, unstable centre of gravity (COG), fluid sloshing in tanks, and adapting to changing payload conditions. Ensuring stability and precision in flight, as well as developing adaptive control mechanisms, are crucial to optimising UAV performance in agricultural applications.

## 3.1 Mapping

Unmanned Aerial Vehicles (UAVs) have become indispensable tools for agricultural mapping, allowing the creation of detailed spatial representations of fields and landscapes. These maps provide critical information on topography, land cover, and vegetation distribution, supporting precision agriculture practices [28]. As seen in Fig. 1, UAVs generate high-resolution digital surface models (DSMs) and orthoimages, which are essential for applications such as volume estimation, field boundary delineation, and land cover classification.

Accurate navigation and flight control are fundamental to achieving the precision required for agricultural mapping. Advanced control algorithms, including robust and adaptive controllers, ensure stability and responsiveness of the UAV, allowing them to navigate complex topographies and avoid obstacles effectively [46, 47]. These control systems enable UAVs to perform reliable data collection even in challenging environments, such as rural areas with unreliable GPS signals [48]. The integration of specialised sensors, such as RGB and LiDAR, enhances the capabilities of

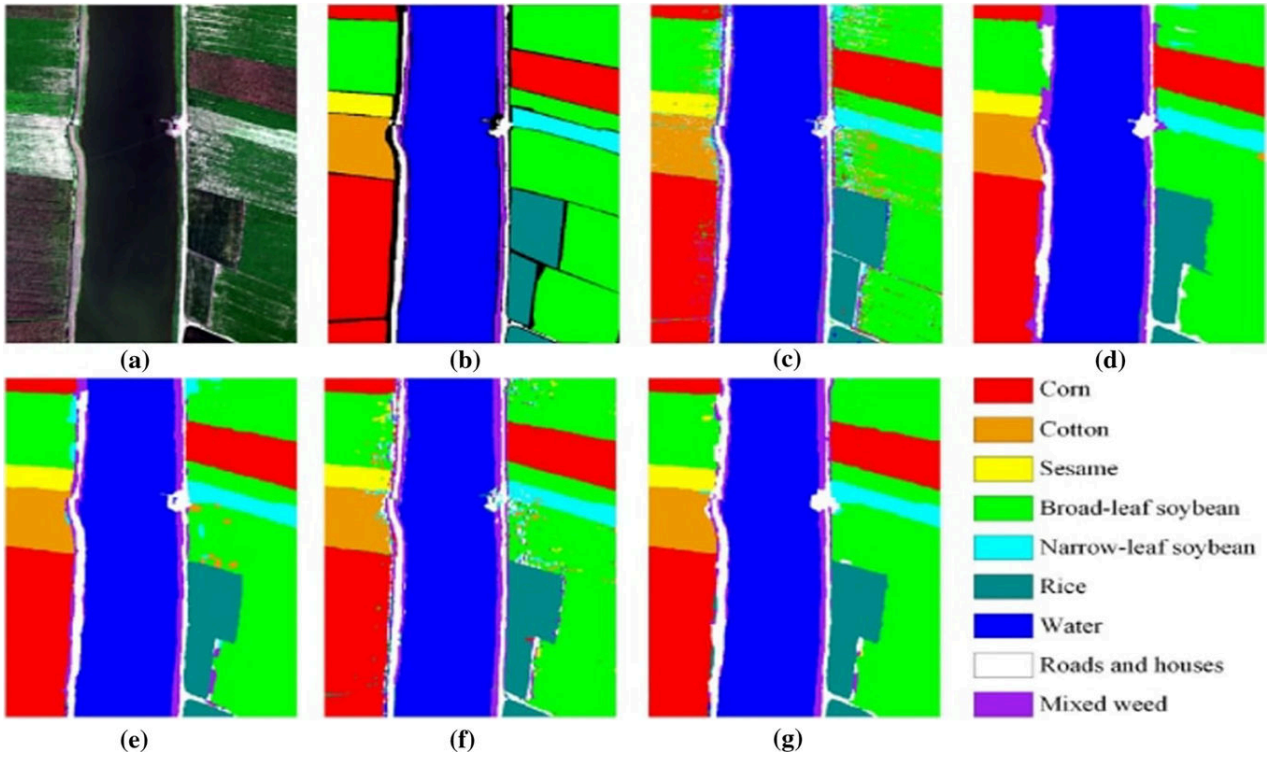



Figure 1: Comparison of different algorithms to classify various crop types a True-color image, b Ground-truth image, c SVM, d FNEA-OO, e SVRFMC, f Benchmark CNN, and g CNNCRF [45]

UAVs for mapping applications. For example, LiDAR equipped UAVs can accurately map canopy height and biomass, providing detailed data for crop management [49]. Similarly, photogrammetric techniques, such as those developed by Liu et al. (2021), eliminate the need for ground control points (GCPs), improving mapping efficiency and accuracy in inaccessible areas [50].

Autonomous mapping and route planning are critical for UAVs operating in agricultural settings. Cooperative multi-UAV coordination, as demonstrated by Guerra et al. (2023), allows UAVs to share information dynamically, improving navigation and task assignment in complex

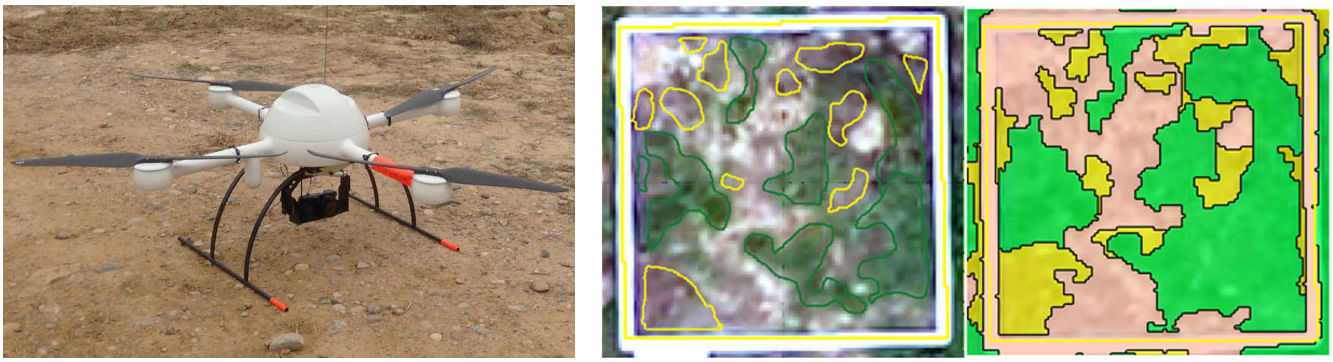
environments [46]. Effective path planning ensures that UAVs can navigate within crop rows or between field boundaries, as shown by Gao et al. (2020) with their colour depth fusion segmentation approach [51].

Recent developments focus on the combination of UAV data with satellite imagery for large-scale agricultural mapping. Ibrahima et al. (2024) demonstrated the integration of UAV and Sentinel-2 imagery to estimate the cover of the millet fraction (FCover) in heterogeneous landscapes in Senegal [52]. This approach exemplifies the potential of UAVs as complementary tools in broader agricultural mapping systems.

In summary, UAV mapping is the cornerstone of precision agriculture, providing detailed spatial representations that support efficient and sustainable farming practices. Future advancements in UAV control systems and sensor integration will further enhance mapping capabilities, paving the way for fully autonomous, high-precision agricultural UAVs.

## 3.2 Sensing and Monitoring

The integration of advanced sensors in UAVs has revolutionised agricultural monitoring, allowing real-time tracking of critical parameters such as crop health, soil moisture, and environmental conditions [53, 54, 55]. As seen in Fig. 2, UAVs equipped with multispectral and thermal cameras can capture high-quality actionable data, empowering farmers to make informed decisions that optimise crop management and maximise yield [57].



(a) (b) (c)

Figure 2: (a) The UAV used in the investigation (b) Ground-truth data for one sampling frame; (c) Classified map for the sampling frame (Ground is yellow coloured and vegetation is green coloured). [56].

Effective control strategies are essential for stabilising UAVs during data acquisition and harmonising sensor output. Techniques such as sensor fusion and real-time data processing enhance UAV capabilities, enabling rapid and relevant insights that support precision agriculture at every stage [58]. UAVs are versatile tools that facilitate applications such as disease detection, yield estimation, and weed management [59].

Commercial off-the-shelf (COTS) sensors, including thermal and multispectral cameras, have expanded UAV capabilities for agricultural monitoring. Thermal imaging, for example, can reveal variations in soil and plant moisture levels, while multispectral sensors capture crop health indicators at various wavelengths [60]. These sensors enable image-based analyses at the pixel level,

creating detailed mosaics that map field health and soil characteristics [61].

UAVs play a critical role in remote monitoring, a key component of autonomous agricultural systems. By measuring chlorophyll content through light absorption, UAVs provide early indicators of crop ripening and general health, allowing farmers to address nutrient deficiencies or disease threats proactively [12]. Various mapping algorithms facilitate virtual sensing, enabling UAVs to conduct noninvasive continuous field monitoring in vast agricultural areas [62, 63].

Collaborations with other data sources, such as satellite imagery and ground-based robotics, improve UAV functionality by broadening the scope and improving the accuracy of agricultural monitoring. Multi-sensor approaches enable UAVs to assess crop health, weed presence, and development across RGB, multispectral, and thermal bands [64, 65]. Analysing specific wavelengths helps UAVs identify weed density and distribution, allowing targeted interventions and improved herbicide application efficiency [66, 67].

Researchers have also explored UAV technology for high-throughput phenotyping to support sustainable agriculture. Ampatzidis et al. (2019) used UAVs to assess the impacts of rootstock on citrus tree health, demonstrating the potential of UAVs for large-scale phenotyping in commercial settings [68]. This approach helps identify crop phenotypes that are resistant to environmental stressors, a key factor in sustainable farming [69].

In conclusion, UAVs equipped with advanced sensing and monitoring technologies are indispensable in precision agriculture. Their ability to deliver high-quality real-time data enables farmers to make data-driven decisions that improve crop management and increase productivity. As UAV sensing technology advances, these systems will play an increasingly central role in enabling sustainable and efficient agricultural practices around the world.

## 3.3 Spraying

According to the Food and Agriculture Organisation (FAO), the global use of pesticides in agriculture in 2022 was 3.70 million tonnes [70]. This high level of pesticide usage raises concerns about the environmental impact and efficiency of conventional spraying methods, which often result in significant chemical waste and uniform distribution [71, 72]. In response, UAVs are increasingly being used in precision agriculture due to their capacity for efficient, safe, and cost-effective pesticide application (see Fig. 3). UAVs are versatile, capable of adapting to different topographies, cultivation methods, and stages of crop growth, making them valuable tools in modern agricultural practices [73, 74].

UAV-based spraying offers several advantages over traditional methods. UAVs provide time and cost savings, precise targeting, and a safer experience for operators by reducing their exposure to hazardous chemicals. Furthermore, UAVs can achieve complete coverage reaching both sides of plant leaves, which is challenging with ground-based spraying equipment [76]. Studies show that spot spraying based on UAVs, which targets specific weeds identified through high-resolution cameras, can reduce pesticide usage by up to 90%, exemplifying the potential for resource efficiency in precision agriculture [77, 78].

Recent technological advancements further expand UAV spraying capabilities. For example, the hybrid drone-rover system introduced by Kant et al. (2023) enables UAVs to switch between aerial and ground operations, optimising efficiency in complex terrains and improving pesticide application accuracy across different crop types [79]. Qin et al. (2021) developed an AI-driven UAV system that autonomously identifies target areas and performs precision spraying in palm plan-

(a) (b)

Figure 3: (a) Customized electrical-powered unmanned aerial vehicle (UAV) (b) Spraying deposition on WSP paper [75].

tations, significantly reducing pesticide consumption while ensuring application accuracy through real-time decision making [80]. Similarly, Singh et al. (2024) used a 2D LIDAR-based canopy detection system to guide UAVs in smart spraying applications, offering high precision and efficiency in vegetation mapping and targeted spraying [81]. Qin et al. (2021) investigated path optimisation for UAV spraying systems, addressing drift and improving coverage accuracy, which is particularly beneficial in large agricultural fields [82].

Despite these advantages, the aerial spraying process with UAVs is complex and requires sophisticated control systems to ensure efficiency and accuracy. UAVs face challenges related to payload stability, environmental factors such as wind, and dynamic flight dynamics during spraying operations. Small UAVs, in particular, are prone to payload-induced instabilities, which can compromise spraying accuracy. Adaptive control systems that respond to real-time feedback are essential to maintain stability under varying conditions, such as changing payload distributions and environmental disturbances [83, 73].

Studies emphasise the importance of control algorithms that can dynamically adjust UAV flight parameters to maintain a consistent spray pattern and compensate for payload changes, such as fluctuating liquid levels in the spray tank. Integrating adaptive control frameworks and advanced sensing technologies is crucial to optimise spray performance and ensure accurate application of pesticides in variable agricultural environments [74, 84].

In summary, UAVs for agricultural spraying represent a transformative advancement in precision agriculture, providing accurate and efficient pesticide applications while reducing environmental impact. However, the complexity of UAV spraying operations demands continuous advancements in control technology. By addressing control challenges, UAV spraying can achieve greater operational safety, resource efficiency, and adaptability to various agricultural needs.

# 4 Agriculture Spraying Control Challenges

The efficiency of UAV-based spraying is a crucial factor in aerial agricultural applications, where structural constraints of UAVs, such as limited payload capacity, small size, and battery life, present ongoing challenges [83]. These limitations restrict the operational range and duration of UAVs, necessitating advanced control methodologies to maximise efficiency and precision. Furthermore, effective manipulation of UAV capabilities and control strategies can mitigate these limitations, enhancing overall performance and adaptability in diverse agricultural environments [85].

One commonly adopted solution to limited payload capacity is the use of high concentration pesticides. Although this addresses payload restrictions, it also introduces secondary issues such as phytotoxicity, leaf tissue damage, and chemical burns to plants due to the high concentration of chemicals. Such challenges underscore the need for precision spray control systems that can accurately regulate pesticide distribution, ensuring the correct dosage is applied across varying crop types without causing adverse effects [86]. Achieving this level of control requires sophisticated methodologies, including adaptive control, sensor integration, and real-time monitoring, to adjust UAV operations based on changing field conditions and crop requirements.

This section explores and analyses the selected control challenges in agricultural spraying based on UAVs, focussing on how advanced control technologies are applied to overcome these inherent limitations, stabilise UAV operations, and improve spraying accuracy. Studies in this area have highlighted the importance of integrating control systems that can dynamically respond to payload variations, wind disturbances, and environmental factors, which are essential for the precise, efficient and safe application of pesticides in modern precision agriculture.

## 4.1 General UAV Challenges in Urban Area

### 4.1.1 Wind Disturbances

Wind disturbances present a significant challenge for UAV operations in agricultural, rural, and forested environments, where wind conditions are often variable and unpredictable. For UAVs that conduct precision spraying, mapping, or payload transport, stability under wind disturbances is crucial to maintaining accuracy and safety. Unpredictable gusts and varying wind patterns in open agricultural fields or in uneven forest terrain introduce lateral forces and rotational disturbances that can impact UAV flight paths and compromise mission objectives if not properly managed[87].

In rural and agricultural settings, wind disturbances disrupt the uniform application of pesticides and fertilisers, creating drift effects that hinder even distribution. Studies emphasise that optimising UAV altitude and dynamically adjusting position can mitigate wind-induced drift, ensuring more consistent pesticide application while minimising off-target effects [88, 89]. Furthermore, integrating real-time wind data from sensors like anemometers and GPS-enabled drift sensors into UAV control systems enables micro-adjustments to counteract wind forces, enhancing stability and accuracy during operation.

Model Reference Adaptive Control (MRAC) and Sliding Mode Control (SMC) have been effectively adapted for UAVs to maintain stability under variable wind conditions [90]. These methods allow UAVs to dynamically adjust flight parameters, reducing drift and maintaining accurate trajectory tracking even in challenging wind conditions. For more turbulent disturbances, Model Predictive Control (MPC)-based methods offer an advanced approach by predicting and compen-

sating for wind influences on UAV trajectories, although they require higher computational power, limiting real-time applications in some cases [69].

In recent years, machine learning-based control systems have shown promise in managing wind disturbances by learning from historical data to predict and pre-emptively adjust for common wind patterns. For example, reinforcement learning (RL) algorithms have shown improved control performance in high-disturbance environments, enabling UAVs to better handle lateral wind forces and navigate efficiently in forested and agricultural terrains [91]. Furthermore, route optimisation algorithms designed specifically for agricultural applications can minimise UAV exposure to cross-winds by planning paths that avoid high-wind areas, thus conserving energy and ensuring efficient spray coverage across fields [21].

In conclusion, managing wind disturbances is vital for UAVs operating in agricultural and rural environments. Using adaptive control techniques, integrating advanced sensing technologies and using machine learning, UAVs can achieve stable and precise operations despite wind variability, ultimately enhancing their reliability and performance in precision agriculture.

### 4.1.2 Mission Planning

Multi-rotor UAVs are widely recognised for their maneuverability and portability, making them highly effective for navigating complex environments. These UAVs can optimise flight paths by minimising turning angles and achieving maximum roll and pitch angles for efficient mission execution. However, determining the optimal shortest path for multi-rotor UAVs is a challenging task, as it requires balancing feasibility, safety, energy consumption, and computational efficiency. These complexities arise due to the inherent nonlinear dynamics of UAVs and the constraints imposed by real-world applications. A taxonomy diagram for the path planning algorithms can be seen in Fig. 4.

A mission planning framework tailored for precision agriculture is presented in [93]. This approach leverages a multi-agent system with an improved federal architecture, incorporating captain, sub-captain, and normal agents to enhance coordination and task execution. The model ensures seamless UAV operation by considering boundary conditions that allow UAVs to return to farming areas when necessary. To address mission planning as a multiobjective optimisation problem, the MP-PSOGA algorithm is employed, which integrates particle swarm optimisation and genetic algorithms. The algorithm achieves rapid convergence and effectively determines Pareto optimal solutions. A coalition mechanism further improves UAV cooperation by facilitating dynamic re-planning and mission auction processes, enhancing system robustness and adaptability.

Coverage Path Planning (CPP) is another critical aspect of mission planning, particularly for applications such as precision agriculture and search-and-rescue operations. In [94], an improved version of the grid-based Spanning Tree Coverage (STC) algorithm is proposed, utilising Simulated Annealing for optimisation. The Discrete Area Partitioning (DARP) algorithm is then applied to allocate grid sections to UAVs based on their operational capabilities. Implemented within a robust software platform, the proposed method was validated through field experiments, demonstrating a significant improvement in mission duration while preserving UAV operational characteristics.

The choice of a UAV platform significantly impacts mission efficiency. A comparative study [95] evaluates three UAV configurations (Q4P Rotor, AGRI-2000, and Q4L-Rotor) for crop monitoring, considering factors such as flight endurance, sensor type, and coverage efficiency. The results indicate that for small-scale fields (5 ha), the Q4P Rotor is optimal, whereas the AGRI-2000 is

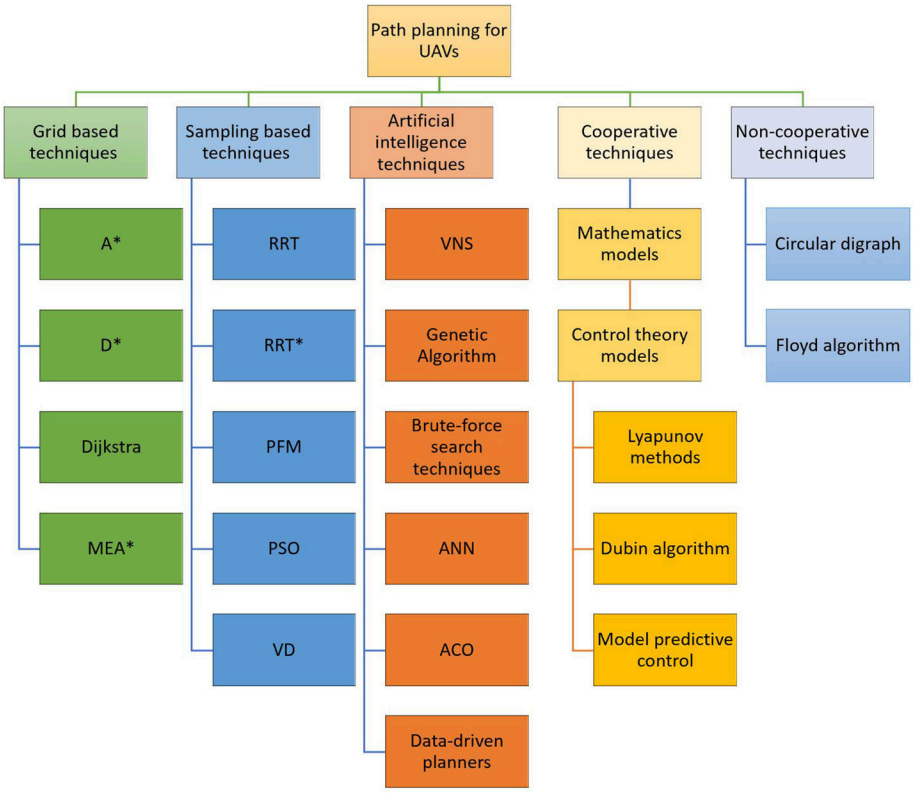



Figure 4: Taxonomy of path-planning techniques [92]

more suitable for larger areas (10-50 ha). Notably, fixed-wing UAVs are deemed unsuitable for low-altitude, high-resolution missions, making multirotor platforms preferable for irregular terrains.

In [96], a path optimisation methodology is introduced utilising a modified genetic algorithm, mhCPPmp. This method improves UAV mission planning by incorporating mobile platforms for in-flight replenishment, leading to a 10-12% improvement in efficiency. The algorithm operates offline, computing the waypoints that UAVs follow during missions. Although effective in reducing flyby costs, limitations include the exclusion of fuelling considerations and real-time path adjustments.

Multi-UAV mission planning is further examined in [97], where the challenge of coordinating multiple UAVs at different Ground Control Stations (GCS) is addressed. The problem is formulated as a temporal Constraint Satisfaction Problem (CSP) and solved using a hybrid MOGA-CSP approach, which combines a Multi-Objective Genetic Algorithm with CSP constraints. This method successfully minimises mission make-up, UAV count, and fuel consumption while ensuring feasible task allocations. Experimental results validate the efficiency of the approach, though increased computational resources are required for more complex mission scenarios.

In [98], a multiphase optimal control framework is developed for agricultural UAV missions, focussing on maximising the coverage area while minimising energy consumption. Using pseudo-spectral numerical methods, the study determines optimal flight speeds for the DJI Phantom 4.0 UAV, highlighting trade-offs between maximum coverage and minimal energy expenditure. Findings suggest that multi-rotor UAVs are best suited for detailed precision agriculture tasks rather than large-scale coverage due to increased power demands at higher speeds.

In [99], a distributed multi-agent planning prototype is introduced for UAV coordination. The

system facilitates real-time adjustments in UAV missions, allowing dynamic task reallocation in response to operational disruptions. The prototype, tested on 3DR IRIS UAVs with Pixhawk PX4 flight controllers, demonstrated robust adaptability for large-scale agricultural monitoring.

Finally, [100] presents a Decision Support System (DSS) designed for Multi-Criteria Multi-Phase Planning Problems (MCMPP). This system ranks mission plans using fuzzy multi-criterion decision-making (MCDM) algorithms, with Fuzzy VIKOR performing best among tested methods. The DSS streamlines operator workload by filtering redundant solutions, enabling efficient decision-making. However, the final selection of the mission remains dependent on the judgment of the operator, highlighting the need for improved interface designs to improve usability.

### 4.1.3 GPS-Denied Navigation and Obstacle Avoidance

Agricultural unmanned aerial vehicles (UAVs) frequently operate in environments where Global Positioning System (GPS) signals are weak or unavailable, such as dense orchards, greenhouses, and remote farmlands. These settings present dynamic obstacles, including tree branches, irrigation systems, and farm infrastructure, complicating autonomous navigation. This subsection examines recent advancements in UAV navigation under GPS-denied conditions, emphasizing adaptive control strategies, obstacle avoidance techniques, and alternative localization methods.

In the absence of GPS, UAVs rely on adaptive control algorithms that compensate for communication constraints and incomplete environmental data. Traditional control methods struggle with limited connectivity to the base station or fluctuating sensor inputs, increasing navigation errors. Recent approaches incorporate predictive modelling, decentralised decision making, feedback mechanisms, probabilistic reasoning, and reinforcement learning to enhance autonomy, improve operational safety, reliability, and efficiency in agricultural applications [101].

Stereo-vision systems play a crucial role in real-time obstacle detection. [102] developed a stereovision framework that allows UAVs to autonomously navigate orchards while avoiding tree branches. Similarly, [103] proposed a UAV exploration system for unknown GPS-denied environments using a Partially Observable Markov Decision Process (POMDP) solver. Their framework, integrated with the TAPIR software and the ABT-POMDP algorithm, dynamically updates an occupancy map via depth sensors, optimising navigation safety and information acquisition.

To address localisation challenges, [104] introduced a multimodal positioning strategy combining Scale-Invariant Feature Transform (SIFT) with Iterative Closest Point (ICP) algorithms. Their approach demonstrated superior accuracy in obstacle avoidance compared to traditional ICP methods while mitigating cumulative drift. However, gravitational acceleration remains a persistent source of error in inertial navigation systems (INS), highlighting the need for further research into vertical drift correction.

Beyond navigation, UAVs are increasingly deployed for precision agricultural tasks such as fruit harvesting. [105] presented *Drone-Bee*, an autonomous aerial manipulation system for GPS-denied environments. This platform employs embedded computing for real-time object detection, positioning, and control, achieving high-precision grasping in cluttered agricultural settings.

With the rise of Global Navigation Satellite System (GNSS) jamming, robust interference detection is critical. [106] developed a detection framework that uses automatic dependent surveillance-broadcast (ADS-B) data, achieving 98.40% accuracy by cross-referencing the Navigation Accuracy Category for Position (NACp) indicators with Horizontal Dilution of Precision (HDOP) values. Future work may focus on accelerating detection speeds and adapting the system for dual-frequency

GNSS receivers.

Environmental landmarks have also been explored for UAV localisation. [107] demonstrated that the integration of vineyard trellises with inertial measurement unit (IMU) data significantly reduced positional uncertainty, offering a viable alternative to GPS-based navigation.

Efficient path planning is essential for UAVs in complex terrains. [108] evaluated cost functions for local path planning, finding that minimising worst-case scenarios at each step reduced the probabilities of failure. Future advancements may incorporate machine learning techniques, such as neural networks or bioinspired algorithms, to further refine collision avoidance strategies.

[109] proposed a vision-based navigation system that integrates differential GPS with deep learning to avoid dynamic obstacles. Their method employs feature extraction and inverse kinematics to optimise flight paths in real time.

For indoor or low-altitude UAV operations, GPS-denied navigation requires alternative solutions. [110] developed an error state Kalman filter (ESKF) integrated with an INS dynamic model and RTAB-Map, achieving high-precision localisation with minimal computational overhead. Meanwhile, studies on low-altitude navigation [111] demonstrated the reliability of artificial landmarks but highlighted weather-induced limitations.

Convolutional Neural Networks (CNNs) have shown promise in aerial visual localisation. A recent review [112] highlighted hybrid models that combine CNNs with recurrent neural networks (RNNs), significantly improving accuracy in settings denied GPS. However, challenges persist in data set scarcity, computational efficiency, and real-time deployment.

Despite progress, key challenges remain:

- **Environmental Interference:** Adverse weather conditions (e.g., fog, rain) degrade sensor performance, necessitating multi-sensor fusion.
- **Computational Constraints:** Neural networks and fuzzy logic systems require extensive datasets and processing power, limiting the applicability in real time.
- **Simulation-to-Reality Gap:** Many algorithms are trained in simulated environments, which requires more realistic virtual datasets.
- **Sensor Synchronisation:** Precise alignment of LiDAR, IMU, and vision sensors is critical for reliable data fusion [113].

Future research should prioritise robust algorithms, efficient computation, and advanced sensor integration to enhance UAV reliability in GPS-denied agricultural operations.

## 4.2 Spraying-Specific Challenges

### 4.2.1 Liquid Tank Modelling

Fluid sloshing in tanks during UAV spraying operations presents significant modelling challenges. The movement of liquid within the tank can cause shifts in the centre of mass of the UAV, resulting in instability and erratic behaviour. For small-scale UAVs, even minor changes in mass distribution can substantially impact flight stability, necessitating accurate modelling of sloshing dynamics [114].

Traditional modelling approaches, such as single and multi-pendulum models, approximate the behaviour of the liquid by representing sloshing as pendular motion [115, 116, 117]. These models offer simplicity and computational efficiency, making them suitable for real-time applications where stability is critical [118].

More detailed approaches employ finite element methods (FEM) to simulate fluid behaviour within a tank, providing a finer resolution of liquid movement and mass shifts [119]. FEM-based models allow for high accuracy in capturing sloshing dynamics but can be computationally intensive, limiting their use in real-time UAV operations.

Smoothed Particle Hydrodynamics (SPH) is another approach that treats the liquid as a collection of particles interacting according to fluid dynamics principles. SPH is particularly useful for simulating free-surface flows and handling complex tank geometries, as demonstrated in applications for aerospace and marine systems [120].

Additionally, models based on multi-mass spring systems provide a compromise between simplicity and accuracy by representing the liquid as a series of interconnected masses and springs [121, 122]. This method captures essential sloshing behaviour while maintaining lower computational requirements, making it applicable to UAV applications where computational resources may be constrained.

Recent studies have introduced advanced modelling techniques to address the complexities of sloshing dynamics. Yano and Terashima [123] developed a trajectory control design method to suppress residual vibration in liquid container transfer systems without directly measuring vibration. Their approach involves shaping the frequency characteristics of the controller using simple structures like notch and low-pass filters, and determining parameters through optimisation with constraints in both time and frequency domains. This method was applied to a liquid container transfer system, demonstrating effective sloshing suppression during high-speed transfers along three-dimensional paths.

Zang et al. [124] proposed two methods to reduce an infinite number of sloshing modes in a moving liquid container. The first method utilises command smoothing to eliminate slosh by targeting the first-mode frequency, while the second combines input shaping and command smoothing. The input shaper reduces slosh for the first mode, and the smoother command suppresses slosh for the third and higher modes. Both methods effectively eliminate transient and residual slosh, with the combined controller achieving a shorter rise time. Simulations and experimental results validated the effectiveness of these methods.

Each modelling technique offers unique benefits depending on the specific application and payload requirements of the UAV. Pendulum-based models and multi-mass spring systems are often preferred for their simplicity in real-time control scenarios, while SPH and FEM are suited for detailed off-line analyses where computational power allows for finer resolution. Advanced methods, such as those proposed by Yano and Terashima [123] and Zang et al. [124], provide robust frameworks for modelling and suppressing sloshing dynamics, enhancing UAV stability and precision in agricultural spraying applications.

### 4.2.2 Center of Gravity (COG)

An unstable centre of gravity (COG) presents a significant challenge for UAVs in agricultural applications, especially when carrying liquid payloads for spraying or transporting slung payloads. In these scenarios, the COG is dynamic, often changing as liquid levels decrease or the payload

moves, leading to instability and complicating flight control. The assumption that the COG coincides with the UAV's geometric centre and remains constant is often unrealistic, as practical applications frequently involve continuous changes in payload distribution. These shifts in COG can result in erratic flight behaviour, reduced manoeuvrability, and an increased risk of errors in the application of pesticides or the transport of the payload[125].

To address the complexities of COG variability, advanced control strategies that dynamically account for changes in the mass distribution are essential. Lee et al. (2017) developed a model for a quad rotor that experiences COG variations due to fluid movement in the payload tank, highlighting the need for robust proportional derivative control (PD) to maintain stability in the presence of liquid-induced COG shifts [126]. Their research emphasises the importance of control methodologies that respond dynamically to COG changes, particularly in agricultural UAVs, where stability is critical for precision.

Furthermore, estimation techniques such as Kalman-Bucy filters, as explored by Stanley and Goodall (2010), provide a framework for predicting and compensating for COG shifts in real time. This approach is highly relevant in applications where COG can shift unpredictably, such as in UAVs that carry liquid payloads with complex motion dynamics [127]. Kalman filtering offers a reliable method for improving control stability and accuracy, which is essential for precision spraying or stable transport of agricultural materials.

Additional approaches, such as the adaptive fault-tolerant control method proposed by Tan et al. (2019), further enhance UAV stability in response to COGs varying over time. Tan's research introduces a control methodology that adapts to COG changes and potential faults, providing a robust framework for UAVs tasked with dynamic payloads or long-duration missions where the mass distribution may vary significantly over time [128]. Similarly, Patel et al. (2018) explored adaptive control methods under variable mass configurations, applicable to UAVs with changing COG due to liquid payload depletion or shifting slung loads, enhancing the responsiveness and flight stability of the UAV [129].

Iqbal et al. (2021) studied COG shifts in airships, which, while different from UAVs, share the challenge of significant COG variation due to heavy payloads. Their findings highlight the relevance of adaptive weight distribution strategies, which could be applied to UAVs that carry large or mobile agricultural payloads that alter the balance and control requirements of the vehicle during flight [130].

In practical applications, COG shifts affect the precision of UAV operations, particularly in tasks such as the application of targeted pesticides, where a consistent and steady flight path is essential for uniform coverage. Tumari et al. (2020) designed a cascade structure with a PID controller to adapt to COG variations, effectively stabilising UAVs under shifting payload conditions. Their study illustrates the potential of structured control approaches to mitigate the instability associated with COG changes, which is critical for agricultural spraying missions where precision and stability directly impact application efficiency and environmental safety [131].

In conclusion, addressing COG variability in UAVs for agricultural spraying and slung payload transport is vital to maintaining operational precision and stability. By integrating advanced estimation techniques, such as Kalman filtering, and adaptive control frameworks, UAVs can dynamically adjust to COG changes, ensuring accurate and reliable performance in complex agricultural environments. These developments not only enhance the reliability of UAVs in precision agriculture, but also expand their potential applications in scenarios where payload dynamics play a central role.

# 5 Control Methodologies

The stability and control of UAVs carrying dynamic payloads, such as liquid-filled pesticide tanks, present unique challenges due to the shift of weight and payload distribution during flight. These variations can cause instability, affecting the manoeuvrability and control of the UAV, which are especially critical in precision agriculture applications where drones must deliver pesticides, fertilisers, or other chemicals with precision and consistency[132].

Carrying payloads with changing weight characteristics is a demanding control problem, particularly in agriculture. The fluid dynamics in a liquid-filled tank creates a shifting centre of gravity (COG), complicating control requirements. Addressing these challenges requires adaptive control strategies capable of dynamically adjusting to changing payload characteristics. Various techniques, including robust non-linear control, adaptive backstepping, decentralised adaptive control, sliding mode control, and machine learning-enhanced control, have been explored to manage these complexities and ensure UAV stability despite dynamic payload variations.

Adaptive backstepping control is essential to manage UAV dynamics with variable payloads [133]. Recent studies such as those by Xinyu et al. [134] and Bhaita et al. [135] utilise adaptive backstepping combined with prescribed performance and Hamiltonian-based approaches to mitigate payload-related disturbances and improve stability. These methodologies are particularly valuable in agricultural UAVs facing fluid dynamics challenges in pesticide tanks, where fluid sloshing can destabilise flight.

The robust non-linear backstepping approach, explored by Zhou et al. [136], integrates finite-time prescribed performance to ensure rapid stabilisation, particularly beneficial in high-disturbance environments such as open agricultural fields. Such techniques ensure that the UAV can adapt to changes in payload and environment, maintaining consistent control and precision during spraying operations.

Model predictive control (MPC) is frequently applied for precise trajectory tracking in UAV systems. Fu et al. [137] introduced a tube-based MPC approach that incorporates MINVO-based obstacle constraints to control the swing of payload and ensure collision avoidance, ideal for UAV navigation in constrained agricultural spaces. In environments with variable obstacles, MPC helps maintain stability of the UAV while following optimised spray paths.

Additional research by Schreier et al. [138] within MRAC frameworks highlights methods to stabilise UAVs under shifting COG, as seen in dynamic agricultural applications where payload characteristics may change frequently. Using MRAC's predictive capabilities, UAVs can better handle fluid motion within pesticide tanks, minimising disruptions to spraying patterns.

Machine learning has shown promise in adaptive control by leveraging historical flight data to improve UAV stability[139]. For instance, Menebo et al. [140] applied neural networks in control systems, allowing UAVs to adjust to environmental disturbances in real time, which is particularly useful in agriculture where payloads and environmental conditions vary. Reinforcement learning (RL)-based approaches, as shown by Estevez et al. [141], optimise route planning and stability management, allowing UAVs to adapt flight paths to complex terrains and variable wind patterns common in agricultural fields.

Sparse Online Gaussian Process (SOGP) with Incremental Backstepping (IBKS), as implemented by Kartal [142], offers real-time learning and adaptation, allowing UAVs to actively counteract sloshing disturbances. The online learning capability of SOGP makes it ideal for unpredictable agricultural environments, providing UAVs with high adaptability without pre-tuning

model parameters.

Sliding Mode Control (SMC) provides resilience under variable disturbances, making it suitable for environments with fluctuating wind and COG shifts. Research by Geronel et al. [143] demonstrates the use of SMC with a robust non-linear approach to stabilise UAVs carrying slung loads. This methodology is particularly beneficial in applications where dynamic payloads create frequent changes in the centre of mass of the UAV, such as agriculture.

SMC has also been combined with adaptive backstepping to improve disturbance rejection in high wind conditions, as shown by Zhang et al. [144]. This hybrid approach is advantageous for UAVs spraying pesticides in large open agricultural areas where environmental disturbances are a constant challenge. Integrating SMC with adaptive control allows UAVs to quickly adjust to changing payloads, improving accuracy in precision agriculture.

Multi-UAV systems have been explored for their potential in large-scale agricultural applications, where cooperative spraying and path planning can improve efficiency[145]. Ju et al. [146] developed control strategies for coordinating multiple UAVs in spraying missions, incorporating adaptive path planning to efficiently distribute tasks. This approach optimises pesticide application, reduces resource consumption, and extends UAV operational time, making it highly applicable to expansive agricultural fields.

In addition, Siddik et al. [147] implemented a decentralised cooperative control framework for multiple UAVs that perform simultaneous operations in agriculture. Using cooperative control, UAVs can dynamically adjust positions and spray patterns, adapting to field conditions and ensuring even pesticide coverage. Multi-agent reinforcement learning further enhances the capability of these systems by enabling each UAV to learn optimal actions based on local environmental feedback, as shown by Khursheed et al. [148] and Xu et al [149].

Wind disturbances are a critical factor that affects UAV stability, particularly in agricultural areas with open fields. Ding et al. [150] integrated model predictive control with optimisation techniques to counteract wind-induced drift, improving UAV trajectory tracking. By employing predictive algorithms that account for environmental changes, UAVs can minimise the effect of lateral forces caused by wind, maintaining consistent spray patterns.

Despite significant advancements in UAV control methodologies for agricultural spraying, several challenges remain. Although adaptive control techniques, such as backstepping and MRAC, effectively manage shifting payload dynamics, most studies rely on simplified fluid models rather than fully integrating real-time liquid motion effects into control strategies. Additionally, while machine learning approaches like reinforcement learning and SOGP enhance UAV adaptability, real-time learning and rapid environmental adaptation remain underexplored. Most adaptive systems require extensive offline training, limiting their responsiveness to unpredictable field conditions.

In addition, multi-UAV coordination presents challenges in scalability and energy efficiency, with limited research on optimising battery consumption and mitigating communication delays in large-scale operations. Wind disturbance rejection strategies, particularly MPC-based techniques, perform well in moderate conditions but require further refinement for extreme weather scenarios, such as heavy gusts and rain. Furthermore, regulatory and safety considerations remain underdeveloped, necessitating fault-tolerant control mechanisms to prevent failures due to sensor malfunctions or unexpected environmental disturbances. Addressing these gaps will be crucial to improving the reliability, efficiency, and autonomy of UAVs for precision agriculture applications.

In conclusion, advanced control methodologies, particularly those that incorporate MPC, adaptive control, sliding mode control, and machine learning, are essential to overcome the complex

control challenges inherent in UAV applications for precision agriculture. These methods provide UAVs with the flexibility, adaptability and resilience needed to navigate the dynamic agricultural environment, optimise spray patterns, and ensure precise and environmentally responsible agricultural practices. The integration of machine learning-enhanced adaptive control with robust control frameworks offers a promising approach to achieving greater stability, accuracy, and efficiency in agricultural UAV applications.

# 6 Conclusion

The integration of Unmanned Aerial Vehicles (UAVs) in agriculture has evolved significantly over the past few decades, offering innovative solutions to enhance precision, efficiency, and sustainability in farming practices. Although UAVs are not a new concept in agriculture - evidenced by the long-standing use of systems such as the R-MAX helicopter in Japan and the widespread adoption of DJI's agricultural UAVs - recent advances in control systems, sensors, and artificial intelligence (AI) have expanded their capabilities and applications. This review has explored the key challenges and advancements in UAV control systems, with a particular focus on agricultural spraying operations, where precision and stability are critical.

One of the primary challenges in agricultural UAV operations is the dynamic nature of the tasks they perform. Spraying operations, for instance, introduce unique control challenges such as liquid sloshing, shifts in the centre of gravity (CoG), and external disturbances such as wind. These factors require advanced control strategies to ensure stable and precise performance. Among the control methodologies reviewed, adaptive control techniques, including backstepping algorithms and machine learning-based approaches, have shown significant promise. These methods enable UAVs to adapt to changing conditions in real time, improving their ability to handle variable payloads and environmental factors.

The applications of UAVs in agriculture go beyond theoretical research and offer practical benefits to farmers and the environment. By enabling precise input applications, reducing chemical usage, and supporting real-time crop monitoring, UAVs contribute to more sustainable and efficient farming practices. However, the full potential of UAVs in agriculture can only be realised through continued innovation and interdisciplinary collaboration. Future research should focus on refining adaptive control algorithms, integrating sensor fusion techniques, and exploring cooperative multi-UAV systems to further enhance autonomy and precision.

In addition to technical advances, there is a need for cross-disciplinary studies that address the broader challenges of UAV adoption in agriculture. For example, research on mission planning, platform design, and regulatory frameworks will play a crucial role in ensuring the safe and effective deployment of UAVs in diverse agricultural settings. Furthermore, the integration of AI and data analytics offers exciting opportunities for the development of intelligent UAV systems capable of autonomous decision-making and task optimisation.

In summary, UAVs have become an essential tool in modern agriculture, based on decades of development and innovation. Although significant progress has been made, ongoing research and collaboration is needed to address the remaining challenges and unlock the full potential of UAVs in agriculture. By combining advanced control methodologies, interdisciplinary research, and practical insights, UAVs can continue to contribute to global food security and sustainable agricultural practices.

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# Comprehensive review of agriculture spraying UAVs challenges and advances: modelling and control

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