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# Potential and Pitfalls of Using Drone Technology in Sustainable Agriculture: An Overview

**S. Rishikesavan[1], P. Kannan[2*], S. Pazhanivelan[2], R. Kumaraperumal[1], N. Sritharan[3], D. Muthumanickam[1], M. Mohamed Roshan Abu Firnass[4], B. Venkatesh[5]**

1- Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
2- Centre for Agricultural Nanotechnology, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
3- Department of Rice, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
4- Department of Soil Science & Agricultural Chemistry, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
5- Department of Civil Engineering, Alagappa Chettiar Government College of Engineering and Technology, Karaikudi, Tamil Nadu, India
(*- Corresponding Author Email: kannan.p@tnau.ac.in)

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## Abstract

Drones have emerged as a promising technology in precision agriculture, supporting Sustainable Development Goals (SDGs) by enhancing sustainable farming practices, improving food security, and reducing environmental impact. This review article is intended to meticulously analyze the multiple applications of drone technology in agriculture, such as crop health monitoring, pesticide and fertilizer spraying, weed control, and data-driven decision-making for farm optimization. It emphasizes the role of drones in precision spraying, promoting targeted interventions, and minimizing environmental impact compared to conventional methods. Drones play a vital role in weed management and crop health assessment. The paper focuses on the importance of data collected by drones to acquire the necessary information for decision-making concerning irrigation, fertilization, and overall farm management. However, using Unmanned Aerial Vehicles (UAVs) in agriculture faces challenges caused by batteries and their life, flight time, and connectivity issues, particularly in remote areas. There are legal challenges whereby regulatory frameworks and restrictions are present in different regions that affect the operation of drones. With the help of continuous research and development initiatives, the challenges depicted above could be solved, and the fullest potential of drones can be tapped for achieving Sustainable Agriculture.

**Keywords:** Crop monitoring, Data-driven decision making, Precision agriculture, Resource optimization, Unmanned Aerial Vehicles (UAVs)

## Introduction

Drones were initially created for military purposes and are also called Unmanned Aerial Vehicles (UAVs) (Zhang *et al.*, 2020), miniature pilotless aircraft, or mini flying robots (Hafeez *et al.*, 2022). UAVs are remotely controlled aircraft equipped with Global Positioning System (GPS) and specialized equipment such as thermal and multispectral sensors. The modern use of drone technology is in military affairs, search and rescue operations, agriculture, surveying



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and mapping, documenting archaeological sites and artifacts, and forest and wildlife protection (Rejeb, Abdollahi, Rejeb, & Treiblmaier, 2022). In the agriculture sector, conventional practices suffer from challenges including high use of chemicals, lack of farm labor, uneven distribution of sprays, environmental pollution, and an inability to reach many farms. These conventional methods burn more cash on pesticide application and are less effective in managing pests and diseases (Hafeez *et al.*, 2022). However, the recent infusion of cutting-edge technologies into agricultural paradigms has inaugurated a paradigm shift characterized by innovation and heightened efficiency in recent years (Puri, Nayyar, & Raja, 2017). The application of mechanistic methods and Artificial Intelligence in farming has ignited an increased rate of innovation and efficiency much earlier than expected (Puri *et al.*, 2017). Among such incipient innovations, Unmanned Aerial Vehicles (UAVs), also known as drones, have emerged as a powerful tool in revolutionizing the agricultural field. According to Nhamo *et al.* (2020), in that regard, drones are capable of capturing accurate and high-resolution images, sending and supplying multiple feeds simultaneously with real-time results, and undertaking numerous operations in agricultural fields. UAVs have the potential to transform traditional remote sensing (RS) systems in which plant monitoring and growth, weed discrimination, crop water stress, disease, and crop yield assessment, and systematic approaches to pest and nutrient management are converted into one real-time or at any given conditional strategy. The equipment depends on the intended use of drones; These include, among other things, cameras, sensors, and control devices.

The use of UAVs in small-scale agriculture, especially in water-stressed areas, is of great value as they provide valuable information for operational decisions at the farm level. It is useful for risk mitigation against crop failure and low yields (Nhamo, Mabhaudhi, & Modi, 2019). Drone data collection is useful to farmers as it can manage pests, decide on resource inputs, and maximise harvests (Olson & Anderson, 2021). Continuous monitoring of crops is to detect small changes that may not be easily visible by the human eye (Delavarpour, Koparan, Nowatzki, Bajwa, & Sun, 2021; Pongnumkul, Chaovalit, & Surasvadi, 2015). UAVs equipped with high-resolution multispectral cameras enable precise monitoring of individual plants, ideal for smallholder farms (Barbedo, 2019). With the help of multispectral images, Normalized Difference Vegetation (NDVI) and Normalized Difference Red Edge (NDRE) indices are developed, offering valuable insights into crop health by assessing solar radiation absorption intensity and other critical factors (Ishihara, Inoue, Ono, Shimizu, & Matsuura, 2015). Besides, thermal cameras add value to UAVs' abilities to measure evapotranspiration and identify water stress (Hoffmann *et al.*, 2016). The spread of UAV use in agriculture is made possible by the reduced cost, with many models now priced affordably, despite additional operational expenses (Barbedo, 2019; Mulero-Pázmány, Stolper, Van Essen, Negro, & Sassen, 2014).

Policies are progressively becoming more balanced, particularly in rural areas where safety and privacy concerns are less pronounced (Barbedo & Koenigkan, 2018). UAVs enable rapid reconnaissance of large rural estates, complementing ground-based sensors and surpassing the resolution limitations of satellite imagery (Barbedo, 2019; Gabriel *et al.*, 2017). Advancements in imaging sensors enable high-resolution aerial images even at high altitudes, making it easier to detect problems early (Barbedo, 2019). In addition, the use of UAVs is becoming more and more convenient as automated flight missions and offline planning are possible. Drones play a critical role in assessing risks and damage in disaster-affected agricultural areas and providing timely information for efficient response and recovery efforts (Dileep, Navaneeth, Ullagaddi, & Danti, 2020; Ren, Zhang, Cai, Sun, & Cao, 2020). Even when monitoring the impacts of climate change on agriculture, drones provide valuable data for adaptive resource management and crop selection, thereby increasing resilience to future challenges (Ukhurebor *et al.*, 2022).

Drones are a practical, rapid, and affordable technology that can gather information on crop emergence, inform decisions about replanting, and assist in predicting yield by combining high-resolution data with algorithms for machine learning. This system generates output with 97% accuracy using data acquired through drones and photogrammetry. Drones equipped with LiDAR sensors make it possible to estimate biomass changes in tree and crop biomass through differential height measurements.

Drone applications for agriculture correspond with multiple Sustainable Development Goals (SDGs). Improving crop monitoring and yield forecasts helps achieve SDG 2: Zero Hunger, by boosting food security. SDG 12: Responsible Consumption and Production is supported by precision spraying and data-driven interventions, since they minimize environmental effects using less pesticide and fertilizer. Additionally, by maintaining crop health and optimizing resource use, drones assist SDG 13: Climate Action, through climate-smart agriculture. SDG 15: Life on Land is related to the work in enhancing land management and protecting ecosystems, and SDG 9: Industry, Innovation, and Infrastructure is related to the promotion of agricultural innovation. Collectively, these technologies support sustainable farming methods that help achieve several SDGs.

The structure of this review is meticulously framed to offer a comprehensive understanding of the usage of drones in sustainable agriculture. The articles relevant to our study were identified using appropriate keywords from Google Scholar, and the same research literature was collected from the corresponding journal website. The main goal of this review article is to examine the inherent potentials and pitfalls associated with the use of drone technology to support sustainable agricultural practices. The aim is to reveal the latent benefits and limitations of the use of drones in agroecosystems by analyzing and evaluating the potential of unmanned aerial vehicle technology in various agricultural environments and functions, including crop monitoring, pest control, precision agriculture, and sustainable land management. Additionally, we have conducted an in-depth analysis of the technical and regulatory dynamics that govern the adoption and use of drone technology in agriculture, providing insights into the myriad opportunities and obstacles that chart the path to fully realizing its transformative potential.

## Types of drones used in agriculture

In the field of agriculture, three primary classifications of Unmanned Aerial Vehicles (UAVs) are prevalent: Fixed-wing, Helicopter, and Multi-copter, plus hybrid drones (Fig. 1) (Velusamy *et al.*, 2022). This implies a need to consider factors such as the type of UAV model that will suit a given application and the financial resources available. For example, blimps comprise huge useful characteristics, including hovering capabilities, vertical flight, and lifting power. However, their utility is hampered by inherent limitations such as reduced speed and compromised stability in adverse weather conditions, which can impede accurate data acquisition (Liebisch, Kirchgessner, Schneider, Walter, & Hund, 2015).

Fixed-wing drones have immobile wings shaped like airfoils, generating lift as the vehicle attains a specific velocity (Marinello, Pezzuolo, Chiumenti, & Sartori, 2016). These UAVs are distinguished by their high-speed flight capabilities and prolonged endurance in the air (Herwitz *et al.*, 2004). Typically capable of achieving velocities ranging between 25-45 mph, fixed-wing drones exhibit a significant coverage capacity, spanning from 500 to 750 acres per hour, contingent upon battery specifications (Puri *et al.*, 2017).

Helicopters, on the other hand, are rotorcraft with a single set of spinning rotor blades attached to a central mast, creating lift, and often incorporating a tail or counter-central rotor for yaw control. Unmanned helicopters possess the capability of vertical takeoff and landing, sideways flight, and hovering. They boast a larger payload capacity compared to multi-rotor UAVs, enabling them to accommodate sizable sensors like LiDAR (Chapman *et al.*, 2014). Multi-copters, alternatively, are rotorcraft equipped with multiple rotor blades, typically between 4 to 8, facilitating enhanced control over movements encompassing yaw, roll, and pitch (Marinello *et al.*, 2016). This configuration grants multi-copters heightened agility and maneuverability, making them particularly well-suited for applications demanding intricate aerial operations within confined spaces or complex environments.

Multi-copters UAVs provide advantages such as cost-effectiveness, hover capability, and minimal requirements for take-off and landing, rendering them extensively utilized for Field-Based Photography (FBP). However, they are accompanied by notable drawbacks, including limited flight duration, diminished payload capacity, and vulnerability to adverse weather conditions (Peña, Torres-Sánchez, de Castro, Kelly, & López-Granados, 2013).

Hybrid drones combine the beneficial features of both multirotor and fixed-wing models. They can take off and land vertically, like multirotor drones, while also featuring fixed wings that enable efficient gliding and coverage over extensive areas. This versatile design makes hybrid drones ideal for a wide range of agricultural applications (Garg, 2022). The advantages, disadvantages, and applications of fixed-wing drones, helicopters, and multi-copters are delineated in Table 1.

## Crop-specific Standard Operating Procedures (SOPs) for drone applications

Standard Operating Procedures (SOPs) tailored to specific crops and environmental conditions are crucial for maximizing agricultural productivity and ensuring sustainable practices. The Ministry of Agriculture and Farmer's Welfare, supported by the Government of India (GOI), has taken progressive measures to promote the use of drones in agriculture. As part of these efforts, GOI has developed Standard Operating Procedures (SOPs) for drone spraying in agriculture. Crops are grown in various environments, so SOPs must be developed to address ecological factors like temperature, humidity, wind speed, terrain, and other environmental factors. These SOPs are focused on drone specifications such as flying speed and height above the crop canopy, sprayer factors including the type of nozzle, spray width, crop factors, volume of the canopy and growth stage, water and pesticide rates, and the best time to spray. Furthermore, they also consider the weather of the particular region and the climate zone where the chemicals will be used, to obtain the best efficiency of pesticides and to minimize the negative impact on crops. The flying height of the drone over the crop canopy depends on aspects like the total mass of the drone, the downforce impact over the crop canopy, and the type of sprayer.

Fixed-wing Helicopter (Zhang *et al.*,2020) Multi-copter

**Fig. 1.** Primary types of UAVs

**Table 1-** Benefits, drawbacks, and applications of fixed-wing drones, helicopters, and multi-copters

| Drone type | Payload & applications in agriculture | Benefits | Drawbacks | Reference |
|---|---|---|---|---|
| Fixed wing | 1. Large-scale spraying<br>2. Monitoring extensive areas<br>3. Crop growth assessment<br>4. Crop health status<br>5. Fertilizer and pesticide spraying | 1. Streamlined architecture<br>2. Simplified maintenance<br>3. Increased flight speed<br>4. Enhanced energy efficiency<br>5. Superior survivability | 1. Restricted accessibility<br>2. Reduced wind resistance<br>3. Challenges in launching and landing<br>4. Required more training<br>5. High initial and maintenance costs | (Hafeez *et al.*, 2022) |
| Helicopters | 1. Spraying capacity (5 to 30 L)<br>2. Pesticide spray<br>3. Estimation of crop height<br>4. Soil and field analysis<br>5. Crop classification | 1. Longer flying time<br>2. Increased speed<br>3. Robust durability<br>4. Accessibility to remote locations and operating on petrol<br>5. Vertical take-off, landing, hovering, forward, and backward | 1. Incomplete coverage during spraying<br>2. Increased weight<br>3. Expensive setup<br>4. Stability issues<br>5. High initial and maintenance costs | (Hafeez *et al.*, 2022; Sinha, 2020) |
| Multi-copter | 1. Spraying capacity (up to 100 L)<br>2. Local field requirements and crop stress, targeted pesticide spraying<br>3. Monitoring small fields, estimating crop height<br>4. Conducting soil and field analysis<br>5. Integral aspects of the overall agricultural approach | 1. Tailored site management<br>2. Low-altitude flight and improved stability<br>3. Stable flight, increased payload, and slow capability<br>4. Vertical take-off and UAV swarms<br>5. Pre-programmed flight plans and improved accessibility | 1.Limited by slow speed<br>2.Payload weight capacity<br>3.Complex architecture and challenging maintenance procedures<br>4.Limited flight capabilities<br>5.Unstable in windy weather | (Hafeez *et al.*, 2022; Ferraz, Santiago, Bruzi, & Vilela; 2024; Sinha, 2020) |
| Hybrid drone | 1. Spraying capacity (10 to 100 L)<br>2. Field mapping and monitoring<br>3. Long-range missions<br>4. Monitoring crop conditions, detecting pests, diseases, and nutrient deficiencies through aerial surveys<br>5. Assessing soil health by capturing data on moisture levels, organic matter, and overall soil conditions | 1. Longer time in flying<br>2. large-area coverage, precise and flexible<br>3. Adaptable for diverse farming tasks<br>4. Provides detailed imagery and data for informed decision-making | 1. High initial and maintenance costs<br>2. Required more training<br>3. More complex and require frequent maintenance<br>4. Gasoline-powered hybrid drones can cause noise and air pollution when powered | (Hoffmann *et al.*, 2016; Kalaiselvi *et al.*, 2024) |

To ensure operational efficiency and safety concerns, the drone is programmed to work at the optimal level below the crop canopy to avoid drift when spraying. Nevertheless, it is indispensable to keep the vertical clearance above the crop because the thrust of the drone may be detrimental to the crop. Hence, the choice of the appropriate height for operation has been highlighted in the SOPs. Likewise, the speed of the flying of the drone is associated with the pattern of the spray distribution and it should also be optimized. Several experiments have been conducted to standardize the drone application among different crops, delineated in Table 2.

## Rice

Rice is the most important staple crop and has been cultivated in a large area in Asia and as well as on other continents. It requires an SOP for drone application to achieve the fullest potential of drones in rice crop monitoring. Hence, Tamil Nadu Agricultural University in Coimbatore, India conducted a pioneering study on using drones for pesticide spraying in rice fields. They utilized a hexacopter drone with specific parameters, including a payload of 16 L and a fuel capacity of 3.5 L. Through this study, they established a standard operational protocol for drone-enabled pesticide application, determining that a flight height of 1.5-2.0 m, a flight speed of 5 m $s^{-1}$, coverage area of 4 min $acre^{-1}$, and wind speed below 5 km $h^{-1}$ were optimal conditions for effective pesticide spraying (Subramanian, Pazhanivelan, Srinivasan, Santhi, & Sathiah, 2021). Similarly, research carried out in the rice fields of China explored miniaturized UAVs for efficient pesticide spray without crop damage. Standardized parameters (1.5 m height, 5 m $s^{-1}$ speed) ensured effective delivery and uniform distribution (CV = 23%), yielding high insecticidal efficacy (92-74%). UAV spraying surpassed conventional methods, enhancing pesticide activity duration (Qin *et al.*, 2016). Another experiment was conducted to standardize the fertilizer and pesticide spraying in a paddy field in Parit Keladi Village, Indonesia. Impact assessments on paddy growth, including leaf length and tiller number, were carried out. The drone achieved ground coverage of 6-7.5 m at a 4 m altitude, equipped with four nozzles and a 1.6 L $min^{-1}$ spraying flow rate. This study introduced drone technology to conventional paddy fields, significant in Indonesia and other Asian countries (Panjaitan, Dewi, Hendri, Wicaksono, & Priyatman, 2022). Hence, these experiments ensure optimal drone functions such as effective pesticide delivery, fertilizer application, and better crop production.

## Maize

Maize is also one of the important staple crops in the world. The Agricultural Research Station of the Tamil Nadu Agricultural University, situated at Bhavanisagar, Tamil Nadu, India, conducted a study on delivering nutrients to maize via foliar spray using battery-operated and fuel-operated drones and a traditional knapsack hand sprayer. They utilized battery-operated and fuel-operated drones with specific parameters. A battery-operated drone features a 10-liter tank and a 16000 mAh battery, with a spraying width of 3.5 meters and a flying height of 0.75 to 1 meter above the crop canopy. The fuel-operated drone has a 16-liter tank and a 4-liter fuel tank, with a spraying width of 4 meters and a flying height of 0.75 to 1 meter above the crop canopy. UAV spraying surpassed conventional methods and enhanced biometric attributes. The benefits of drone spraying include a reduction in the amount and expenses of nutrients, lower cost compared to traditional spraying techniques, and significantly decreased spray fluid necessity (Kaniska *et al.*, 2022).

## Cotton

Cotton is an important commercial crop, and to ensure improved penetration and uniform distribution of applied chemicals, UAV spraying requires optimizing flight height, spray volume, and droplet size. In Xinjiang, experiments were conducted, and the parameters selected include spray volume (8.7, 12, and 15 L $ha^{-1}$ in 2018; 18, 22.5, and 30 L $ha^{-1}$ in 2019), droplet size (100, 150, and 200 µm in both years), and flight height (1, 2, and 3 m in 2018 only). The study found that adjusting flight height, spray volume, and droplet size notably affects spray penetration. Lowering drone flight height, increasing spray volume, and enlarging droplet size enhance droplet distribution at the lower cotton canopy. However, flight parameters minimally affect droplet distribution uniformity (P. Chen *et al.*, 2021). Understanding droplet distribution and drift and cotton aphid and spider mite control effectiveness and cotton leaf adhesion and absorption in UAV spraying. Droplets were collected using Kromekote card and filter paper, and parameters such as droplet density, coverage rate, deposition, and drift percentage were statistically examined. The combined results showed that at a UAV flight altitude of 2 meters, droplet uniformity, coverage rate, deposition, and drift ability increased (Lou *et al.*, 2018).

## Sugarcane

The ideal spraying parameters for sugarcane crops were determined to be a spray volume of 15 L ha$^{-1}$, a flight height of 3 m, and a flight velocity of 4 m s$^{-1}$ (Zhang *et al.*, 2020). The most effective spraying parameters identified were a flight height of 6.0 m and a flight velocity of 2.5 m s$^{-1}$, resulting in a minimal pesticide usage of 15.38 L ha$^{-1}$. These findings offer valuable insights for selecting suitable parameters for single-rotor drone applications in sugarcane protection (Zhang *et al.*, 2021). The artificial neural network has proven to be a reliable predictive model for non-destructive nitrogen estimation in sugarcane using drone-captured aerial images (Hosseini, Masoudi, Sajadiye, & Abdanan Mehdizadeh, 2021).

## Pulses

For Black gram, the Agricultural Research Station, Tamil Nadu Agricultural University located at Bhavanisagar, Tamil Nadu, India, experimented with applying nutrients to black gram via foliar spray using battery-operated and fuel-operated drones with the traditional knapsack hand sprayer. (P. Chen *et al.*, 2021; Freeman & Freeland, 2015) utilized battery-operated and fuel-operated drones with specific parameters. A battery-operated drone features a 10-liter tank and a 16000 mAh battery, with a spraying width of 4 meters and a flying height of 1 meter above the crop canopy. The fuel-operated drone has a 16-liter tank and a 4-liter fuel tank, with a spraying width of 4 meters and a flying height of 1 meter above the crop canopy. Drone spraying showed greater efficiency than manual knapsack sprayers (Nandhini, Thiyagarajan, & Somasundaram, 2022). While for Green gram, Anbil Dharmalingam Agricultural College and Research Institute, in Tiruchirappalli, India conducted a study to assess the viability of utilizing drones for foliar nutrient spraying on the growth characteristics, yield, and economic aspects of green gram cultivation and used drones with specific parameters including a tank capacity of 10 L, a Spraying width of 3.5 m, and a Flight height of 1.5 m (Dayana, Ramesh, Avudaithai, Sebastian, & Selvaraj, 2022).

## Papaya

The effectiveness of droplet distribution utilizing an unmanned aerial vehicle across various application rates (12.0, 15.0, and 18.0 L ha$^{-1}$) and spray nozzles (XR110015 and MGA015) targeting different layers (upper, middle, and lower) of papaya fruit clusters was assessed. They utilized a DJI T10 drone with specific parameters, including a payload of 10 L, a spraying width (m) of 3-5.5, a flight height of 2.5 meters above the crop canopy, and a flight speed of 5.0 m s$^{-1}$ (Ribeiro, Vitória, Soprani Júnior, Chen, & Lan, 2023). Thus, the results of these experiments help in standardizing the protocols and operating procedures for drone application among different crops and it could increase and improve crop productivity.

**Table 2-** Application of UAVs with the set of parameters (spraying width, flight height, flight speed, and nozzle type) in various crops

| Crop | UAV type | Application | Payload (tank capacity (L)) | Nozzle type | Spraying width (m) | Flight speed (m $s^{-1}$) | Flying height (m) above the crop canopy | Reference |
|---|---|---|---|---|---|---|---|---|
| Rice | Hexacopter Drone | Pesticide | 16 | - | - | 5 | 1.5-2 | (Subramanian *et al.*, 2021) |
| Rice | Hy-B-15l (Single Rotor) | Pesticide | 15 | Tee Jet 110067 | 4-5 | 5 | 1.5 | (Qin *et al.*, 2016) |
| Rice | Hexacopter Drone | Fertilizer and Pesticide | 16 | - | - | 4 | 2 | (Panjaitan *et al.*, 2022) |
| Maize | Battery-Operated | Nutrients | 10 | Flood Jet | 3.5 | 4-5 | 0.75 to 1 | (Kaniska *et al.*, 2022) |
| Maize | Fuel-Operated | Nutrients | 16 | Flood Jet & Atomizer | 4 | 4-5 | 0.75 to 1 | (Kaniska *et al.*, 2022) |
| Cotton | Xag P Series Plant Protection Uav | - | 15 | Centrifugal Nozzles | 3.5 | - | 1-3 | (P. Chen *et al.*, 2021) |
| Cotton | | Fertilizer and Pesticide | 10 | Centrifugal Nozzles | 1.5 – 3 | 1-8 | 2 | (Lou *et al.*, 2018) |
| Sugarcane | Quad-Rotor Electric Drone | Pesticide | 15 | Centrifugal Nozzles | - | 4 | 3 | (Zhang *et al.*, 2020) |
| Sugarcane | Single-Rotor Drone | Pesticide | | Centrifugal Nozzle | - | 2-3 | 6 (above the ground level) | (Zhang *et al.*, 2020) |
| Sugarcane | Tiger Drone | Fertilizer | 10 | Flat Fan | | 3-6 | | (Koondee, Saengprachathanarug, Posom, Watyotha, & Wongphati 2019) |
| Black Gram | Battery-Operated | Nutrients | 10 | Flood Jet | 4 | 4-5 | 1 | (Nandhini *et al.*, 2022) |
| Black Gram | Fuel-Operated | Nutrients | 16 | Flood Jet & Atomizer | 4 | 4-5 | 1 | (Nandhini *et al.*, 2022) |
| Greengram | Ad610d | Nutrients | 10 | Flat Fan Standard Nozzle | 3.5 | - | 1.5 | (Dayana *et al.*, 2022) |
| Papaya | Dji T10 | | 10 | XR110015 and MGA015) | 3-5.5 | 5 | 2.5 | (Ribeiro *et al.*, 2023) |

## Potentials of drone technology

Advanced data analytics and technology are coupled to optimize resources and agronomic practices, encompassing the potential of drones as a critical facet in sustainable agricultural systems (Vairavan, Kamble, Durgude, Ingle, & Pugazenthi, 2024). The increasing accessibility of drone technology is enabling its integration into precision agriculture practices (Dutta, Singh, Mondal, Paul, & Patra, 2023) (Fig. 2). In precision agriculture (PA), drones are utilized to efficiently monitor various stages of crop growth, facilitating the collection and processing of extensive data about crop health across different developmental stages (Shafi *et al.*, 2019). Precision agriculture utilizes a range of technologies, including the Global Positioning System, Geographic Information System, Remote Sensing, sensors, and data analysis, to gather information on crop conditions and soil diversity. Subsequently, this data can be employed to make well-informed decisions regarding the application of inputs such as water, fertilizer, and pesticides (Vairavan *et al.*, 2024). Unmanned Aerial Vehicles (UAVs) are frequently employed in agriculture to conduct Remote Sensing (RS) tasks, such as surveying crop fields and overseeing livestock (Freeman & Freeland, 2015). Specifically, UAVs equipped with multispectral cameras have proven valuable in assessing crop yields, tracking crop height, mapping weed distribution, and monitoring biomass. Additionally, the use of UAVs with high-resolution cameras and various sensors allows for the observation of topographic alterations within watersheds (Ali, Al-Ani, Eamus, & Tan, 2017).

These surveys provide precise coordinates of contaminations, which can be integrated into water quality monitoring plans for additional sampling. In addition to remote sensing (RS) and Unmanned Aerial Vehicles (UAVs), specialized sub-systems can be employed for on-site measurements of water quality parameters such as pH, dissolved oxygen, electrical conductivity, and temperature in surface waters (Capolupo, Kooistra, Berendonk, Boccia, & Suomalainen, 2015). Complementing on-site measurements, the utilization of tailor-made water collection devices can enhance water sample collection, thereby improving water quality monitoring in larger water bodies.

Precision agriculture applications using UAVs cover a wide range of tasks, including crop health monitoring, pesticide and fertilizer spraying, vegetation growth monitoring for yield estimation, vegetation health monitoring and pest management, irrigation management, water stress assessment, nutrient monitoring and deficiency analysis, evapotranspiration (ET) estimation, and weed control.

## Crop monitoring and management

In precision agriculture, drones play an instrumental role in tasks such as field mapping and crop condition monitoring, as depicted in Fig. 3 (Hafeez *et al.*, 2022). Equipped with a diverse array of advanced sensors, including multispectral and thermal cameras, drones facilitate the collection of remote sensing data, enabling comprehensive observation of crops. Analysis of this data allows for the evaluation of crop health, detection of diseases or pests, and tracking of overall plant growth. Leveraging drones for crop monitoring and cutting-edge management empowers farmers to make data-driven decisions regarding irrigation, fertilization, and pest management (Delavarpour *et al.*, 2021). Drones equipped with various sensors, including those for visible, near-infrared (NIR), and thermal infrared wavelengths, enable continuous monitoring of crops throughout the growing season. By computing multispectral indices derived from reflection patterns, these drones can assess crop conditions including water stress, nutrient deficiencies, pest infestations, and diseases. Even before visible symptoms manifest, early detection facilitates timely intervention and serves as an early warning system for effective remedial actions (Simelli & Tsagaris, 2015). Unmanned Aerial Vehicles (UAVs) can survey extensive hectares of fields in a single flight. Thermal and multispectral cameras are mounted on the underside of the quadcopter to capture observations and record the reflectance of the vegetation canopy (Colomina & Molina, 2014).

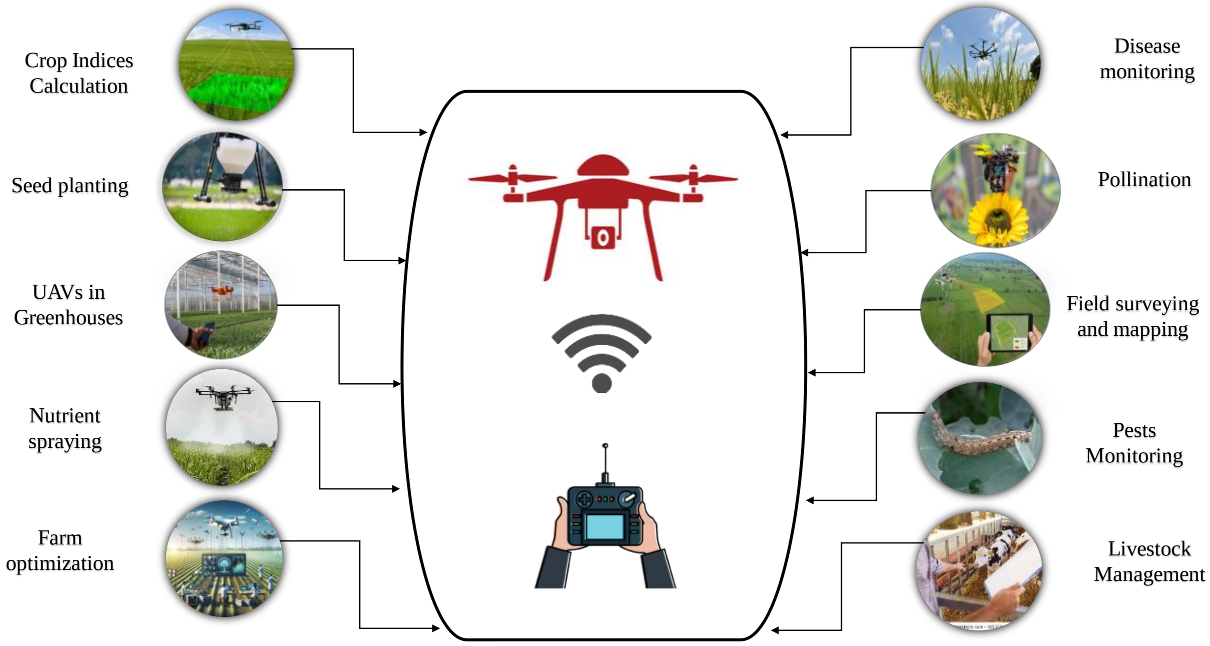


**Fig. 2.** Application of drone technology in precision agriculture

The camera captures one image per second, storing it in onboard memory before transmitting it to the ground station via telemetry (Delavarpour *et al.*, 2021). A UAV-based monitoring system addresses precision management in crop production (Ni *et al.*, 2017). The UAV crop-growth monitoring system comprises three primary components: the UAV platform, the crop-growth sensor affixed to the UAV, and the ground-based data processor (Delavarpour *et al.*, 2021). The crop-growth sensor, mounted on the UAV platform, records reflection spectra from the crop canopy in real-time. Subsequently, the ground-based data processor wirelessly receives and processes this data. By estimating indices such as NDVI, RVI, LNA, LAI, and LDW, and providing critical insights into crop growth, the processor contributes to crop growth and health-monitoring models (Ma, Zhu, Zhou, Zou, & Zhao, 2019). These technological advancements will provide farmers with more precise and comprehensive information about their crops, leading to increased yields, reduced input costs, and enhanced overall farm profitability (Ennouri & Kallel, 2019).

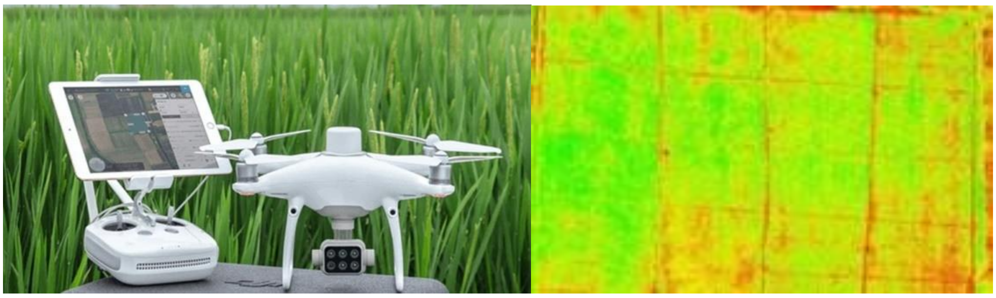

**Fig. 3**. DJI P4 Multispectral drone and vegetative indices (NDVI)
(Source: https://www.dji.com/global/p4-multispectral)

## Nutrient and Deficiency Monitoring

In agricultural contexts, ensuring plants receive optimal nutrient levels is crucial for achieving robust growth and maximizing yields. Essential nutrients such as nitrogen, phosphorus, and potassium play distinct roles; nitrogen promotes leaf growth, phosphorus supports root and stem strength, and potassium enhances disease resistance. The NDVI Index aids in pinpointing areas of crop stress, enabling targeted intervention.

UAVs equipped with near-infrared (NIR) and multispectral imagery facilitate early detection of management zones, allowing proactive measures before visible symptoms manifest. Currently, nutritional assessments often rely on subjective visual inspections or labor-intensive laboratory leaf analyses, both of which have limitations in accuracy and efficiency (Dezordi, Aquino, Aquino, Clemente, & Assunção, 2016).

Alternative methods such as the chlorophyll meter (SPAD) provide indirect estimates, albeit with drawbacks including time consumption and potential inaccuracies (Balasubramaniam & Ananthi, 2016; Jia, Chen, Zhang, Buerkert, & Römheld, 2004; Nauš, Prokopová, Řebíček, & Špundová, 2010). Consequently, there is a growing emphasis on exploring novel approaches for identifying and quantifying plant nutritional deficiencies (Ali *et al.*, 2017).

Many studies in the literature derive vegetation indices (VI) from imagery and establish correlations with nutrient content through regression models, often employing linear models. Although less prevalent, other categories of variables have also been incorporated into regression models, such as the spectra of average reflectance (Capolupo *et al.*, 2015), selected spectral bands (Severtson *et al.*, 2016), color features (Yakushev & Kanash, 2016), and principal components (Berni, Zarco-Tejada, Suárez, & Fereres, 2009).

## Field surveying and mapping

Field surveys using drones have become a vital tool for efficient and precise data collection in agriculture (Rejeb *et al.*, 2022). Drones can capture high-resolution imagery and detailed data on crop health, soil conditions, and topography, providing insights that were previously challenging to obtain on a large scale (Inoue, Ito, & Yonezawa, 2020). With advanced sensors, including multispectral, thermal, and LiDAR, drones can assess factors like plant stress, moisture levels, and canopy cover in real time (Olson & Anderson, 2021). Unmanned aerial vehicles (UAVs) equipped with LiDAR and GNSS sensors to enhance agricultural field mapping. It describes the development of a UAV-based mapping system designed to assess crop height and volume, providing a high-resolution view of field conditions, which is particularly beneficial for precision agriculture (Christiansen, Laursen, Jørgensen, Skovsen, & Gislum, 2017)

These UAV-based surveys allow for the rapid identification of issues such as pest infestations, nutrient deficiencies, and water stress. By generating 2D and 3D maps, drones help in creating site-specific management plans, enabling farmers to make data-driven decisions on fertilization, irrigation, and crop protection (Kim, Kim, & Sim, 2019).This approach not only reduces the time and labor associated with traditional field surveys but also enhances precision, leading to increased productivity and sustainability in agriculture (Aslan, Durdu, Sabanci, Ropelewska, & Gültekin, 2022).

## Site-specific nutrient management

In an agricultural context, the application of fertilizers and chemicals is crucial for crop health and yield optimization. Drones have revolutionized precision agriculture, particularly through specialized applications such as precision spraying (Mogili & Deepak, 2018). UAVs, with advanced capabilities like GPS, autonomous flight control, real-time image transmission, and various sensors, efficiently gather high-resolution spatial data for rapid analysis. They are capable of performing regular surveillance and monitoring abnormal conditions (Chen *et al.*, 2021). Drones offer the capability to deliver chemicals such as fertilizers and pesticides, adjusting quantities based on spatial crop variability and pest severity. Integrating UAVs with sprayer systems supports accurate, site-specific application in extensive crop fields, necessitating the use of heavy-lift UAVs for larger spraying areas (Sarghini & De Vivo, 2017). The lightweight and inexpensive Quadcopter (QC) system, also referred to as an Unmanned Aerial Vehicle (UAV), was proposed by researchers (Kedari, Lohagaonkar, Nimbokar, Palve, & Yevale, 2016).

Researchers have proposed lightweight and cost-effective quadcopter (QC) systems for indoor and outdoor crop spraying, autonomously controlled via Android devices. Leveraging machine learning algorithms ensures precise identification and treatment of insect pests, enabling targeted interventions without compromising healthy crops (Mogili & Deepak, 2018). These drones not only reduce the need for pesticides but also minimize environmental impact, offering improved efficiency and cost-effectiveness compared to conventional spraying methods (García-Munguía *et al*., 2024).

Utilizing drones for precise interventions allows farmers to apply fertilizers, pesticides, and herbicides with exceptional accuracy. This targeted approach minimizes the use of chemicals, leading to cost savings and a reduced environmental footprint compared to conventional widespread spraying methods (Puri *et al.*, 2017). Moreover, drones can be automated to fly independently over designated regions, pinpointing areas of interest by assessing crop health factors like moisture, nutrition, and pest presence. The data gathered offers crucial insights for proactive crop management, empowering farmers with enhanced control and understanding, and fostering sustainable and efficient agricultural practices (Delavarpour *et al.*, 2021).

Advancements in technology have introduced drones to agriculture, offering an innovative and efficient method to reduce chemical usage and promote smart farming, minimizing potential environmental impacts (Bongiovanni & Lowenberg-DeBoer, 2004). Reduction of chemical dependency in agriculture is just one of the advantages of drone technology; it also facilitates enhanced crop monitoring, early pest and disease identification, and efficient land mapping for improved resource management (Hafeez *et al.*, 2022). Incorporating drone technology into agriculture reduces reliance on chemicals and advocates for sustainable and resource-efficient farming methods, ultimately yielding positive environmental outcomes (Talaviya, Shah, Patel, Yagnik, & Shah, 2020).

## Water conservation and soil health

Multiple factors contribute to water stress in crops, and characterizing this stress can be difficult (Berni *et al.*, 2009). Derived variables from thermal images often depend on subtle temperature fluctuations to identify stresses and other phenomena. Consequently, thresholds and regression equations established under specific conditions typically do not apply under even slightly different circumstances. Scientists employed a variety of sensors and modeling techniques to assess instances of water stress. The deployment of drones fitted with specialized sensors can be used to calculate these indices, which could help in the monitoring of water stress. Using multispectral, hyperspectral, or thermal infrared imagery, vegetation indices (NDVI, GNDVI, etc.), the difference between canopy and air temperatures (Tc- Ta) or direct canopy temperature (Dutta & Goswami, 2020), and crop water stress index (CWSI) can be calculated.

Drones are also instrumental in monitoring soil health, capturing detailed images and data to evaluate factors such as erosion, compaction, and nutrient levels. Utilizing drone-supplied data for decision-making allows farmers to improve soil fertility and overall health, promoting sustainable long-term growth (M. Tahat, Alananbeh, Othman, & Leskovar, 2020). Additionally, drones facilitate the acquisition of valuable data and insights, enabling farmers to make informed decisions regarding soil management strategies, ultimately enhancing soil health and productivity (Merwe, Burchfield, Witt, Price, & Sharda, 2020).

## Evapotranspiration (ET) estimation

Evapotranspiration (ET) is a vital process that involves water transfer from the land to the atmosphere through soil evaporation and plant transpiration. With careful concerns about water scarcity, population growth, and climate change, the estimation of evapotranspiration has become a significant focus in agricultural research. Evapotranspiration estimates vary based on the specific functions of different types of unmanned aerial vehicles (UAVs). Fixed-wing UAVs are ideal for large-scale fields because of their two-hour average flying time. In contrast, quadcopters are used for quick missions in smaller fields because of their shorter flying duration, around 30 minutes (Dutta & Goswami, 2020). When utilized as remote sensing platforms, UAVs introduce new research challenges, including drone image processing and flight path planning. An example includes using a fixed-wing UAV to gather thermal data for estimating ET through two-source energy balance models (Hoffmann *et al.*, 2016). Unmanned aerial vehicles (UAVs) can reduce these temporal and spatial constraints. The UAVs can be equipped with lightweight sensors and cameras to capture high-resolution pictures. The spatial resolution of UAV photographs can reach the centimeter level, compared to satellite imagery. Additionally, UAVs can fly whenever needed, allowing for high-temporal images. So, various UAV-based techniques are used for evapotranspiration (Niu, Zhao, Wang, & Chen, 2019). Utah State University developed an airborne digital system to gather multispectral and thermal images for evapotranspiration estimation (Xia *et al.*, 2016). These cameras have the following spectral bands: Near-infrared (NIR) (0.780 µm- 0.820 µm), Blue (0.465 µm- 0.475 µm), Green (0.545 µm- 0.555 µm), and Red (0.645 µm- 0.655 µm). UAV platforms with lightweight sensors can give higher quality, and higher spatial and temporal resolution images as compared to other satellite-based remote sensing techniques (Niu *et al.*, 2019).

## Decision-making system for farm optimization

Agricultural remote sensing proves highly beneficial by enabling the comprehensive observation of crops on a broad scale, employing a synoptic, remote, and non-invasive approach. Typically, this technology employs sensors mounted on Unmanned Aerial Vehicles (UAVs) to capture the reflected or emitted electromagnetic radiation from plants (Weiss, Jacob, & Duveiller, 2020). The collected data is then processed to generate valuable insights and products. These insights encompass various characteristics of the agricultural system, showcasing their spatial and temporal variations. Functional traits refer to the biochemical, morphological, phenological, physiological, and structural features that govern the performance or fitness of organisms, particularly plants (Weiss *et al.*, 2020). Plant traits, categorized as typological, biological, physical, structural, geometrical, or chemical, exhibit variations across plant species and locations. Remote sensing (RS) establishes a crucial link with traits such as leaf area index, chlorophyll content, and soil moisture (Martos, Ahmad, Cartujo, & Ordoñez, 2021). Accurate interpretation relies on factors like crop phenology, type, soil characteristics, weather, and more.

Remote sensing yields key information products like plant density, leaf biochemical content, and soil moisture, aiding in assessments of crop health, disease, irrigation timing, nutrient status, and yield predictions. This data is crucial for interpreting crop health, disease incidence, irrigation needs, nutrient deficiencies, and yield predictions (Weiss *et al.*, 2020). With the global population on the rise, frequent shifts in climate patterns, and limited resources, meeting the food demands of the current population has become a formidable challenge (Kamilaris & Prenafeta-Boldú, 2018). Precision agriculture, also referred to as smart farming, has emerged as an innovative solution to address the existing sustainability issues in agriculture. The integration of drone technology in precision agriculture facilitates sophisticated analytics and data-centric decision-making, leading to optimized farm operations (Gopal, Singh, & Aggarwal, 2021). This acquired knowledge enables farmers to make well-informed decisions regarding irrigation schedules, nutrient management, and pest control, ultimately enhancing productivity and minimizing waste. Additionally, the application of advanced analytics aids in identifying trends and patterns within the collected data, empowering proactive and timely interventions to mitigate risks and maximize crop yields (Sishodia, Ray, & Singh, 2020).

## Crop protection

### Data-driven disease detection

Crop diseases, whether fungal, bacterial, or viral, pose significant threats to agricultural productivity. Timely detection enables proactive measures such as removing infected plants to prevent spread. Image-based tools are instrumental, especially when manual assessment is impractical, unreliable, or inaccessible, with UAVs enhancing surveillance capabilities (Ziya, Mehmet, & Yusuf, 2018). RGB and multispectral images have traditionally been utilized, with ongoing exploration into hyperspectral and thermal imagery (Calderón Madrid, Navas Cortés, Lucena León, & Zarco-Tejada, 2013; Dash, Watt, Pearse, Heaphy, & Dungey, 2017). Drones equipped with multispectral sensors monitor wheat crops, identifying fungal diseases like rust and powdery mildew early. This allows for targeted fungicide applications, reducing chemical use and protecting crop health (Joshi, Sandhu, Dhillon, Chen, & Bohara, 2024). Thermal imaging, in particular, aids in detecting water stress induced by specific diseases. UAVs equipped with infrared cameras offer detailed insights into plant internal structures (Hardin & Jensen, 2011), capturing various data types such as visual, thermal, and infrared with precision. Integration of this data into analytics platforms facilitates actionable insights and predictive capabilities, supporting sustainable decision-making (Baradaran Motie, Saeidirad, & Jafarian, 2023; Lee, Sudduth, & Zhou, 2024; Lu, Dai, Miao, & Kusnierek, 2024; Manfreda *et al.*, 2018; Zhao *et al.*, 2024).

### Pest surveillance and management

The combination of a sprayer system mounted on a UAV for pesticide spraying presents a promising opportunity for effective pest management and vector control. This integrated solution offers precise site-specific application, particularly beneficial for extensive crop fields. To cover large areas efficiently, heavy-lift UAVs become essential for the spraying operation (Sarghini & De Vivo, 2017). The spraying drone has various components (Fig. 4) and Drones with an integrated spraying system flow chart are displayed in Figure 5. The effectiveness of the spraying system, when attached to the UAV, is enhanced by the use of a PWM (Pulse Width Modulation) controller in pesticide applications (Huang, Hoffmann, Lan, Wu, & Fritz, 2009). A prototype is being designed to create a UAV capable of adjusting the mean diameter droplet size up to 300mm. The growing popularity of UAVs in spraying operations is attributed to their speed and precision (Huang, Reddy, Fletcher, & Pennington, 2018). On the contrary, crop quality may be compromised due to issues such as inadequate coverage during spraying, overlapping in crop areas, and ineffective treatment of the outer edges of the field. To address these challenges, a control loop algorithm was implemented in agriculture operations, employing a swarm of UAVs to handle the precise spraying of pesticides (Yao, Jiang, Zhiyao, Shuaishuai, & Quan, 2016). These unmanned aerial vehicles take responsibility for overcoming the mentioned factors and ensuring more effective and uniform pesticide application across the entire crop field.

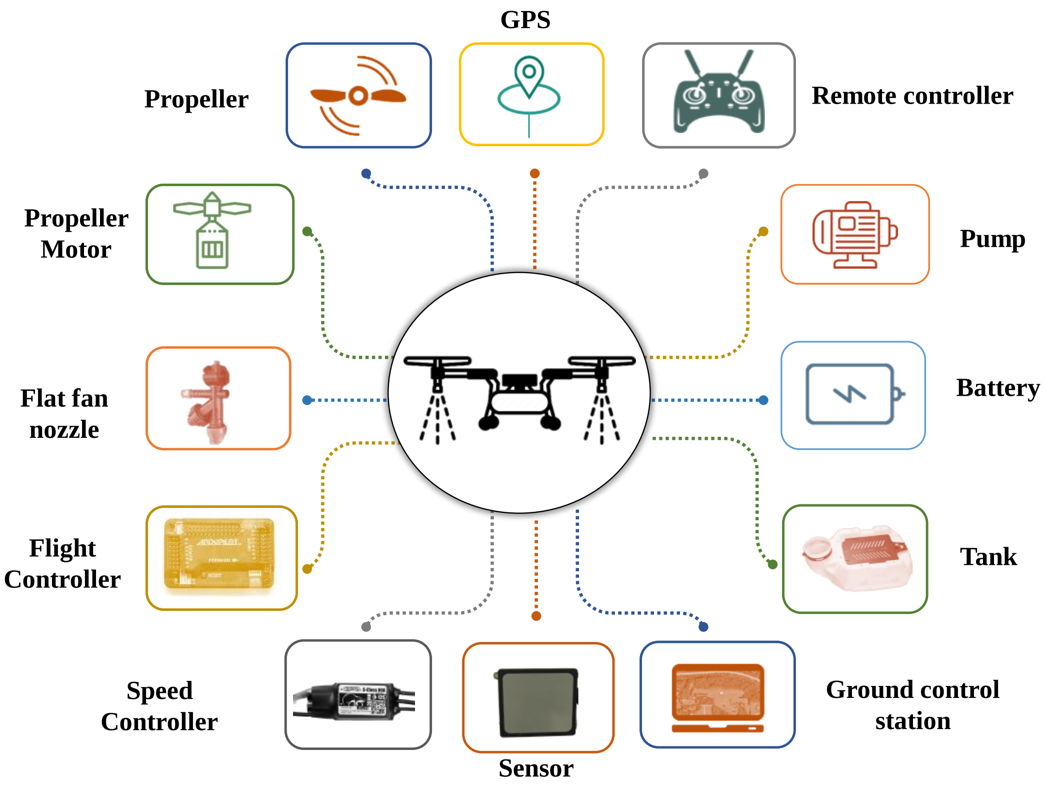


**Fig. 4.** Components of a spraying drone

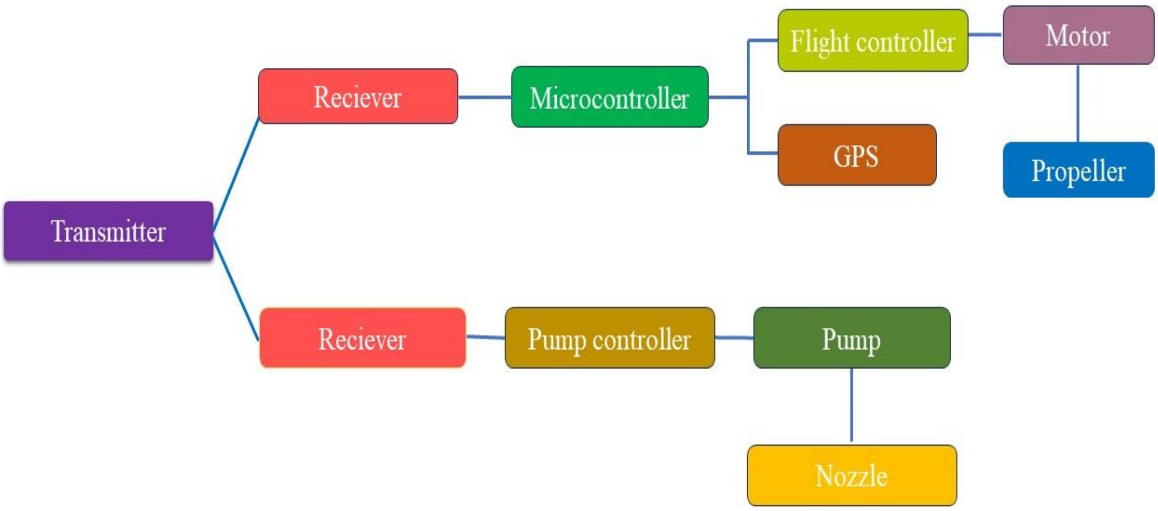


**Fig. 5.** Flow chart of UAVs for pesticide application

## Pollination

Drones offer an appealing solution for crop pollination due to their airborne nature, much like bees, making them well-suited for the task. Drone technology is more accessible than other types of robotics (Wikifactory, 2020). These devices are either directly operated by a pilot, follow a predefined path defined by the arrangement of orchard rows, or use a 3-D representation of the environment produced from a previous pass by scouting drones (Alkhamis, 2021). Among the various techniques being investigated, spraying water-suspended pollen grains using a drone has proven to be an effective method for pollinating date palm trees (Mohamed, Shukla, Keerthika, & Mehta, 2023). Other methods include aerial pollen dispersal and the use of drone-generated air vortices to facilitate pollination directly. These approaches show promise for enhancing pollination in hybrid grain production, as well as in self-compatible crops grown in controlled environments, such as strawberries, tomatoes, peppers, and eggplants (Broussard, Coates, & Martinsen, 2023). Drone pollination serves as a legitimate method of supplementary pollination, capable of enhancing crop yields and supporting a healthy economy (Guzman, Chamberlain, & Elle, 2021).

## Seed planting

Drones are revolutionizing seed planting in agriculture by enhancing precision and efficiency (Khanpara, Patel, Parmar, & Mehta, 2024). Drones can be equipped with sensors and cameras capable of assessing soil conditions and delivering real-time information to farmers. This information can be utilized to optimize seed sowing, ensuring that seeds are planted accurately in terms of location, depth, and density (Paul *et al.*, 2022). Drones enable rapid seed sowing, reducing the working time. They can cover extensive areas rapidly and efficiently, making them especially suitable for farmers managing large fields (Monteiro, de Alencar, Souza, & Leão, 2021). A recent study by Dampage, Navodana, Lakal, and Warusavitharana (2020) highlights the effectiveness of drones in precision seeding, particularly in rice fields. Drones have shown to improve seed placement accuracy, minimize waste, and ensure uniform distribution, which are critical factors in optimizing crop yield and reducing labor.

## Weed Control

Undesirable plants, or weeds, pose challenges in crops by competing for resources, potentially reducing yields. Herbicides are commonly used in conventional farming, but their excessive application may lead to herbicide-resistant weeds, impacting crop growth. Employing hyperspectral images to distinguish between weed spectral signatures with varying glyphosate resistances is explored (Li, Fan, Huang, & Tian, 2016). For example, RGB sensors are used to categorize different types of weeds (Huang *et al.*, 2018).

Drones equipped with hyperspectral sensors were utilized by researchers to track weeds based on the density of leaves and the amount of chlorophyll in the plant canopy (Malenovský, Lucieer, King, Turnbull, & Robinson, 2017). Moreover, weeds poses a significant risk to environmental health. To address these issues, site-specific weed management relies on accurate weed cover maps for precise herbicide spraying. Drones capture field images to create such maps. Utilizing drones for herbicide spraying proves effective for both pre-emergence and post-emergence weed control. It allows spraying in diverse field conditions, including mud, weeds, and various weather conditions. The drone application ensures efficient weedicide use and is user-friendly, portable, and easy to maintain (Dutta & Goswami, 2020).

## UAVs in Greenhouses

In greenhouses, drones serve as compact, efficient tools for monitoring the controlled environment and applying inputs in hard-to-reach areas without disturbing the plants (Erdogan, 2023). UAVs can capture data from nearly any location within the three-dimensional environment of a greenhouse, simplifying and enhancing tasks like localized climate control and crop monitoring. They enable regular, consistent observation of crops, whether weekly or even hourly, allowing for the detection of changes in plant health over time. Aerial perspectives reveal issues such as water stress, soil inconsistencies, and pest infestations more effectively (Aslan *et al.*, 2022). Additionally, advancements in camera technology mean that plant diseases, often invisible to the human eye, can be identified with ease through the use of specialized sensors, including hyperspectral, multispectral, and infrared imaging, allowing for thorough, precise monitoring (Roldán, Joossen, Sanz, Cerro, & Barrientos, 2015).

### Livestock monitoring

In the field of livestock monitoring, drones offer numerous applications for animal husbandry and prove valuable for overseeing extensive herds. Animals on the farm are fitted with sensors or radio-frequency identification (RFID) tags, enabling tracking of feeding patterns and movements. Drones are employed to monitor livestock more frequently, accomplishing this in a shorter time frame without extensive personnel involvement (Ajakaiye, 2023). The concept of remote-sensing fencing or virtual boundaries involves creating a virtual obstacle or security barrier within a specified spatial area, particularly useful in the context of free-range livestock grazing. Equipped with high-resolution infrared cameras, these drones can promptly identify diseased animals based on their heat signatures. Once a diseased animal is detected, it can be isolated from the rest of the herd, allowing for early intervention and treatment. This application positions drones as a tool for precise dairy farming (Rathod & Shinde, 2023).

### Pitfalls in drone technology for sustainable agriculture

Every technology encounters initial limitations, and drones are no exception. Drones in sustainable agriculture face challenges such as limited battery life, connectivity issues in remote areas, and regulatory hurdles. These issues can impact efficiency and effectiveness, but ongoing research aims to overcome these obstacles and maximize drone potential.

### Limited battery life

The main limitation of UAVs is that their maximum flying time is limited by the energy provided by batteries. When drones cover large areas or lengthy flights for data collection purposes, this limitation can cause difficulties (Mohsan *et al.*, 2022). One main constraint concerns technological capabilities, particularly battery life and flight duration (Table 3). Currently, the market has a maximum operating duration of approximately thirty minutes, due in large part to constraints in battery capacity and weight (Dutta & Goswami, 2020). This constraint significantly reduces the area coverage of drones that can be used for spraying, monitoring, and surveying.

**Table 3-** Battery life and flight duration factors affecting flight duration for different types of agricultural drones

| Drone Type | Average battery life (min) | Range of flight duration (min) | Factors affecting flight duration | Reference |
|---|---|---|---|---|
| Multi-rotor drones | 20-30 | 15-45 | Size, weight, motor power, payload weight, weather | (Elouarouar & Medromi, 2022) |
| Fixed-wing drones | 30-60 | 20-90 | Size, battery capacity, motor efficiency, spraying rate, wind | (Elmeseiry, Alshaer, & Ismail, 2021) |
| Vertical Take-Off and Landing (VTOL) drones | 25-40 | 18-50 | Motor type, payload weight, spraying intensity, flying speed | (Dündar, Bilici, & Ünler, 2020) |
| Hybrid drones | 30-45 | 20-60 | Battery capacity, hybrid propulsion efficiency, payload weight, flight distance | (Rajabi, Beigi, & Aghakhani, 2023) |

### Cost scalability

The expense of buying and maintaining agricultural drones is a hurdle for farmers (Emimi, Khaleel, & Alkrash, 2023). The operational cost is also very high, including batteries, sensors, and other equipment that are necessities for operations and may need to be upgraded or replaced regularly. Moreover, there are expenses related to operator training and following rules (Singh, 2023).

#### Technology constraints

There is insufficient knowledge of drone technology among farmers. Many farmers lack exposure to advanced technologies and may find it difficult to understand and trust drone capabilities in precision agriculture (Khaspuria *et al.,* 2024). Additionally, training and knowledge transfer systems are often underdeveloped, making it harder for farmers to gain hands-on experience with drone operations and data interpretation. Addressing this issue requires targeted educational programs, simplified drone interfaces, and partnerships with local agricultural extension services (Dhillon & Moncur, 2023). Such efforts could bridge the knowledge gap, encouraging broader adoption and maximizing the potential benefits of drones in agriculture.

### Data analysis and interpretation

Another significant constraint is data analysis. Drones equipped with hyperspectral sensors often generate many terabytes of data, requiring proper storage, specialized software for processing, and analysis by experts with years of experience. As a result, there is a significant delay between data collection and obtaining results. While multispectral data processing is significantly faster than hyperspectral data processing, accuracy is very low (Yang, Everitt, Bradford, & Murden, 2009). The remote and rural settings of many farms introduce challenges related to connectivity and the real-time processing of intricate sensor data collected by drones (Islam *et al.,* 2021). Agriculture drones collect massive amounts of data, which makes data analysis and interpretation very challenging and time-consuming to handle and analyze (Emimi *et al.,* 2023).

### Adverse weather conditions

The unfavorable weather conditions could restrict the sensing and response of drone activity (Leite-Filho, de Sousa Pontes, & Costa, 2019). Additionally, weather conditions like heavy winds or precipitation pose operational difficulties for drones, particularly those with lighter structures. In general, drone flight missions are designed/planned in such a way as to minimize the above-mentioned constraints. In response to the constraints occurring under unfavorable conditions, may require atmospheric, radiometric, and geometric corrections to require accurate data collection and processing, which are usually application-specific.

### Atmospheric Correction

The sun emits electromagnetic energy (EM) toward Earth, but before it reaches the surface, some of it is absorbed and dispersed by dust and gases in the atmosphere. Aerial imagery for surface reflectance observations is influenced by various processes related to the propagation of electromagnetic radiation within the atmosphere-surface system. Under clear sky conditions, the relevant processes include gaseous absorption, molecular scattering, aerosol scattering and absorption, as well as water surface reflection. In instances of cloudy conditions, the presence of cloud droplets scattering makes surface sensing challenging, with the cloud signal predominantly prevailing. An exception arises when clouds are optically thin or cover only a small portion of the pixel, meaning their impact on pixel reflectance is less than 0.2 (Frouin *et al.*, 2019).

The quality of information derived from aerial image measurements, including vegetation indices, is affected by atmospheric effects. Errors induced by atmospheric effects have the potential to elevate uncertainty by up to 10%, varying depending on the spectral channel (Chen *et al.,* 2021). Moreover, much of the signal received by an imagery sensor from a dark object, like an area experiencing water stress, is attributable to the atmosphere at visible wavelengths, assuming that near-infrared and middle-infrared image data are unaffected by atmospheric scattering effects. Consequently, pixels from dark targets serve as indicators of the amount of upwelling path radiance in that band. To access accurate surface reflectance, the influence of the atmosphere and surface must be eliminated. This necessitates an atmospheric correction model, particularly in scenarios where Vegetation Indices (*D'Sa et al.,* 2016) are utilized in vegetation monitoring and in dark scenes where features like water stress and drought can be masked by atmospheric scatters.

Atmospheric correction removes atmospheric effects, variable solar illumination, sensor viewing geometry, and terrain influence on image reflectance values, thereby determining their true values. Supplying, calibrating, and adjusting for atmospheric conditions at the time of imaging are crucial atmospheric correction prerequisites.

## Radiometric Correction

Radiometric calibration involves establishing the functional relationship between incoming radiation and sensor output, such as Digital Number (Saeed, Younes, Cai, & Cai, 2018). Accurate radiometric calibration is essential for change detection and interpretation, especially when images are captured at different dates, times, locations, or by different sensors. It ensures that changes in the data reflect actual field changes rather than variations in the image acquisition process or conditions (e.g., changes in light intensity). Many image collections involving hyperspectral cameras (e.g., crop phenotyping, disease detection, and yield monitoring) necessitate precise radiometric calibrations.

Several potential solutions can mitigate radiometric variation. Light intensity fluctuates over time due to changes in solar elevation, atmospheric transmittance, and cloud cover. Therefore, conducting image collection flights during periods of minimal solar elevation could reduce radiometric variation in collected data. Additionally, digital camera exposure settings should be carefully chosen based on overall light intensity, either manually or automatically (Hunt, Cavigelli, Daughtry, Mcmurtrey, & Walthall, 2005).

## Geometric correction

Unmanned Aerial Vehicles (UAVs) capture imagery for aerial mapping of agricultural landscapes, but this data often contains geometric distortions arising from various factors such as sensor position variations, platform motion, and Earth's rotation. These distortions, categorized as internal and external factors, lead to inconsistencies in pixel size and inaccurate geographic coordinates of image pixels. Geometric correction is essential to rectify these distortions and ensure the accurate representation of features in the corrected image (Kallimani, Heidarian, van Evert, Rijk, & Kooistra, 2020). By calibrating intrinsic camera parameters like focal distance and lens distortion, geometric correction restores the geometric integrity of the image, facilitating precise spatial analysis.

## Regulatory and legal hurdles

A significant challenge in integrating drones for precision agriculture is ensuring compliance with the diverse regulatory requirements that govern the use of unmanned aerial vehicles (UAVs) in various geographic areas (Table 4). Depending on the geographical area, drones might necessitate registration, licensing, certification, insurance, or permission to operate within specific airspace or over designated land (Stöcker, Bennett, Nex, Gerke, & Zevenbergen, 2017). Moreover, drone pilots need to follow regulations regarding safety, privacy, security, and environmental concerns linked with their drone operations. These rules may differ depending on factors such as the type, size, weight, speed, altitude, and intended use of the drone, emphasizing the necessity for operators to be knowledgeable about and adhere to the relevant legal stipulations and limitations applicable to their particular drone usage and geographic location (Memisoglu, 2019).

Despite drones being utilized in agriculture for the past two decades, regulations about their use in agricultural settings are still nascent worldwide. Although India's utilization of drones in agriculture lags behind that of the US and China, New Delhi has taken proactive measures to establish regulatory frameworks for global drone governance. This initiative is partly driven by the recognition of the potential security implications of drone technology for India, as well as the strategic advantage of leading in this domain to safeguard national interests. At the international level, the International Civil Aviation Organization (ICAO) plays a pivotal role in developing rules and regulations for drone operations, with its initial efforts dating back to 2007. However, it was not until 2011 that the ICAO issued its first set of rules in Circular 328. In December 2018, the Indian government introduced a drone policy facilitating drone applications, particularly for agricultural purposes.

The Directorate General of Civil Aviation (DGCA), and the Government of India (GOI), regulations implicitly permit the use of Remotely Piloted Aircraft Systems (RPAS), i.e., Drone/UAV for agricultural purposes except to spray pesticides until specifically cleared. The DGCA RPAS Guidance Manual provides procedures for the issue of Unique Identification Numbers (Dezordi *et al.*, 2016). Unmanned Aircraft Operator Permits (UAOP) strictly regulate drone operations in various designated areas, including densely populated zones, near airports, during poor weather, and around sensitive facilities. Operators above 18 years old must maintain a visual line of sight, possess a valid license plate and insurance, and refrain from exceeding altitude limits or flying multiple drones simultaneously. Addressing issues related to regulation, ethics, and implementation is imperative, necessitating alignment with existing legal and moral principles and adaptation to rapid technological advancements for the establishment of an effective governance framework for UAVs in India (Swetha, Bharath Kumar, Sanwal Singh, & Urmila, 2024).

In developing countries like Iran, one of the primary barriers to the adoption of drone technology in agriculture is the inability to purchase drones directly from manufacturers, as many drone-producing companies are restricted by international sanctions (Runde, Carter, Bandura, & Ramanujam, 2019). This lack of access limits local farmers' ability to implement drone-based precision agriculture, which could otherwise improve efficiency and crop health assessment.

**Table 4-** Regulatory and legal hurdles

| Challenge | Description | Impact | Reference |
|---|---|---|---|
| Complex permitting processes | Obtaining permits for airspace usage, data collection, and pesticide spraying can be time-consuming and expensive. | Discourages adoption, particularly for small-scale farmers. | (Pathak, Sharma, & Nagar, 2020) |
| Unclear data ownership and privacy | Lack of clarity on data ownership and privacy raises concerns about farmer data being used without their consent. | Farmers hesitate to share sensitive data, hindering its potential for analysis and improvement. | (Altawy & Youssef, 2016) |
| Limited liability and insurance frameworks | Existing frameworks might not adequately address agricultural applications like spraying or livestock monitoring. | Creates uncertainty for farmers and service providers in case of accidents. | (Singh, 2023) |
| Variable regulations across borders | Differing regulations in different countries create challenges for cross-border operations and data sharing. | Hinders global collaboration and technology advancement. | (Pathak *et al.*, 2020) |
| Evolving technology and policy gaps | The rapid evolution of drone technology often outpaces regulatory frameworks. | This leads to hesitant adoption by farmers and discourages innovation by developers. | (Rajagopalan & Krishna, 2018) |

To overcome drone access restrictions in developing countries, encouraging local companies to develop and manufacture drones suitable for agricultural needs could create an alternative supply, and partnering with neighboring countries for technology transfer and drone expertise can also help. Additionally, promoting regional drone production can create self-reliance, reduce dependency, and support precision agriculture, driving sustainable agricultural development.

Agricultural drones make precision farming and resource optimization possible, yet there are drawbacks related to data processing, cost scalability, and regulatory compliance. By overcoming these obstacles, drones in various fields will reach their full potential (Emimi *et al.*, 2023).

## Conclusion

Drone technology holds immense potential for transforming agricultural practices, fostering sustainability, and boosting its efficiency. UAV adoption in agriculture enables the farming community to contribute to the global pursuit of conserving the environment and economic resilience. Its versatile applications span across various domains, including crop health monitoring, precision spraying, data-driven decision-making, and soil health assessment, aligning with the objectives of Sustainable Development Goal 2 (Zero Hunger). The adoption of drones in precision agriculture can also contribute significantly to climate action by curbing greenhouse gas emissions linked to conventional farming methods. Through optimized resource management and reduced reliance on chemical inputs, drones play a vital role in mitigating the agricultural sector's impact on climate change, thereby supporting Sustainable Development Goal 13 (Climate Action). Nonetheless, several challenges impede the widespread adoption of drone technology. Issues such as short battery life and operational limitations during adverse weather conditions present practical barriers that need to be addressed for broader implementation. Regulatory frameworks vary significantly across regions, necessitating adherence to complex guidelines and obtaining permits. This variability, coupled with the high initial cost of drones and the requisite expertise in operation and data analysis, can pose barriers for small-scale farmers.

To overcome these challenges, particularly in developing countries, implementing an agricultural drone subsidy system can be crucial. Such a system would provide financial support to smallholder farmers, reducing the upfront costs associated with acquiring drone technology. By offering subsidies or low-interest loans, governments and international organizations can make drone technology more accessible, enabling even small-scale farmers to benefit from its advantages. Moreover, subsidies could also be directed towards training programs, ensuring that farmers gain the necessary skills to effectively utilize drones and interpret the data they collect.

The undeniable potential benefits of drone technology warrant continued research and development efforts. Key focuses include improving battery life, enhancing sensor capabilities, and streamlining regulations to enhance accessibility and adoption. Additionally, capacity-building initiatives and training programs can equip farmers with the necessary skills and knowledge to effectively leverage this technology. By addressing these challenges and harnessing the transformative power of drones, agriculture can transition towards a future characterized by sustainability and efficiency, thereby ensuring sustainable agriculture and food security. Collaborative approaches involving multiple stakeholders can play a crucial role in ensuring a more effective transfer of UAVs to farmers' fields.

## Future direction

In the realm of agricultural technology, the potential of drone technology stands out prominently, offering efficiency and adaptability across various agricultural operations. For small-scale farmers, the expense of buying and maintaining agricultural drones may be a hurdle. Wider use and accessibility of drone technology depend on its scalability and affordability, including equipment, training, and support services (Emimi *et al.,* 2023). However, challenges such as the high initial investment costs and the necessity for policy reforms remain significant hurdles in popularizing drones and making them accessible to farmers. Moreover, a pressing need exists for robust research endeavors aimed at optimizing operational protocols and validating the efficacy of drone applications. One critical area of investigation involves understanding the intricate dynamics of drone-induced airflow and its impact on liquid distribution during spraying operations.

Recent studies have highlighted the correlation between the rotational speed of drone rotors and the deposition of liquid droplets on various plant surfaces. It has been observed that higher rotor speeds result in a lower deposition of liquid on lower plant levels, indicating the potential for altered distribution patterns due to the airflow generated by drone rotors. Consequently, the efficacy and uniformity of pesticide deposition remain uncertain, underscoring the necessity for detailed research to inform and refine field spraying processes. Beyond this, numerous unresolved issues persist, necessitating further investigation and refinement to realize the full potential of drone technology in agricultural settings. These research endeavors are crucial for addressing existing limitations, enhancing operational efficiency, and ensuring the effective utilization of drone technology for agricultural purposes.

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## Authors Contribution

Kannan Pandian: Conceptualisation, Supervision, Review & editing

Rishikesavan: Writing– original draft, Writing– review & editing

S. Pazhanivelan: Editing– original draft

R. Kumaraperumal: Review & Editing

N. Sritharan: Writing– original draft

D. Muthumanickam: Conceptualisation & editing

M. Mohamed Roshan Abu Firnass: Writing– review & editing

B. Venkatesh: Data analysis and validation

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# مروری بر پتانسیل و مشکلات استفاده از فناوری هواپیماهای بدون سرنشین در کشاورزی پایدار

اس. ریشیکساوان[۱]، پی. کنان[۲*]، اس. پاژانیولان[۲]، آر. کومارپرومال[۱]، ان. شریثارن[۳]، دی. موهومانیکام[۱]، ام. محمد روشن ابو فرناس[٤]، بی. ونکاتش[۵]

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## چکیده

هواپیماهای بدون سرنشین (پهباد) به‌عنوان یک فناوری با پتانسیل بالا در کشاورزی دقیق ظهور کرده‌اند و از اهداف توسعه پایدار (SDGs) با تقویت شیوه‌های کشاورزی پایدار، بهبود امنیت غذایی و کاهش اثرات زیست‌محیطی حمایت می‌کنند. این مقاله مروری بر تحلیل دقیق کاربردهای چندگانه فناوری هواپیماهای بدون سرنشین در کشاورزی، مانند نظارت بر سلامت محصول، پاشش آفت‌کش و کود، کنترل علف‌های هرز و تصمیم‌گیری مبتنی بر داده‌ها برای بهینه‌سازی مزرعه در نظر گرفته شده است. این مقاله بر نقش پهپادها در سمپاشی دقیق، ترویج مداخلات هدفمند و به حداقل رساندن اثرات زیست‌محیطی در مقایسه با روش‌های مرسوم تاکید دارد. هواپیماهای بدون سرنشین نقش حیاتی در مدیریت علف‌های هرز و ارزیابی سلامت محصول دارند. تمرکز این مقاله بر اهمیت داده‌های جمع‌آوری‌شده توسط هواپیماهای بدون سرنشین برای به‌دست آوردن اطلاعات لازم برای تصمیم‌گیری در مورد آبیاری، کوددهی و مدیریت کلی مزرعه است. با این حال، استفاده از وسایل نقلیه هوایی بدون سرنشین (پهپاد) در کشاورزی با چالش‌های ناشی از عمر باتری‌ها، زمان محدود پرواز و مشکلات اتصال، به‌ویژه در مناطق دورافتاده، مواجه است. چالش‌های قانونی، چارچوب‌های نظارتی و محدودیت‌هایی در مناطق مختلف نیز وجود دارد که بر عملکرد هواپیماهای بدون سرنشین تأثیر می‌گذارند. با تحقیق و توسعه مستمر، چالش‌های ارائه‌شده را می‌توان حل کرد و از حداکثر پتانسیل پهپادها برای دستیابی به کشاورزی پایدار استفاده کرد.

**واژه‌های کلیدی:** بهینه‌سازی منابع، تصمیم‌گیری مبتنی بر داده، کشاورزی دقیق، نظارت بر محصول، وسایل نقلیه هوایی بدون سرنشین (پهپاد)

۱- گروه سنجش از دور و GIS، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۲- مرکز نانوفناوری کشاورزی، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۳- گروه برنج، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۴- گروه علوم خاک و شیمی کشاورزی، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۵- گروه مهندسی عمران، دانشکده مهندسی و فناوری دولتی آلاگاپا چتیار، کارائیکودی، تامیل نادو، هند
(*- نویسنده مسئول: Email: kannan.p@tnau.ac.in)

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