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# Applications of unmanned aerial vehicles (UAVS) in agriculture: A review

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## Abstract
The global population is increasing rapidly, leading to a corresponding rise in food demand. Traditional farming practices are often insufficient to meet these growing requirements, necessitating the adoption of advanced automated technologies such as drones. Drone technology not only contributes to fulfilling food demands but also optimizes resource utilization by reducing excessive use of water, pesticides, and herbicides, while helping maintain soil fertility. It enhances manpower efficiency, increases productivity, and improves crop quality. The objective of this paper is to review the diverse applications of drones in agriculture. A comprehensive literature review was conducted to examine existing research worldwide. Findings indicate that drones can support multiple agricultural operations, including crop health monitoring, weed management, evapotranspiration estimation, precision spraying, and overall farm management. The paper concludes by emphasizing the potential benefits of wider adoption of drone technology to improve agricultural outputs and sustainability.

**Keywords:** Drone technology, agriculture, crop health monitoring, weed management, evapotranspiration, precision spraying, soil fertility, smart farming

## Introduction
Agriculture remains the backbone of India's economy; however, the sector still lags in adopting modern technologies compared to developed nations. Countries across the globe have already integrated Unmanned Aerial Vehicles (UAVs) into precision agriculture photogrammetry, and remote sensing thereby enhancing efficiency and reducing the workload of farmers. UAVs are typically equipped with advanced cameras and sensors for crop monitoring, as well as sprayers for pesticide application. Although UAV technology has traditionally been employed in military and civilian domains [5], its application in agriculture has gained momentum in recent years. Technical analyses have highlighted the potential of UAVs in various agricultural operations, including crop monitoring [6], crop height estimation [7], pesticide spraying [8], and soil and field analysis [9]. However, the practical deployment of UAVs largely depends on critical hardware factors such as weight, flight range, payload capacity, configuration, and cost [10].

Initially, drones were often perceived as luxury tools or recreational devices. In agriculture, their potential remained underexplored, to the detriment of farming efficiency and sustainability. Today, drones can operate autonomously through dedicated software that enables flight planning and execution using GPS, while incorporating parameters such as speed, altitude, Region of Interest (ROI), geo-fencing, and fail-safe modes. Compared to manned aircraft, drones offer significant advantages, including high spatial resolution, rapid data acquisition, lower operational costs, and ease of deployment. These features make UAVs particularly suitable for precision agriculture, where vast areas must be monitored and analyzed within minimal timeframes. Advances in miniaturized cameras and sensors such as infrared, multispectral, and sonar technologies have further expanded the scope of UAV applications in modern agriculture.

## Historical Background
The Japanese were the first to successfully implement Unmanned Aerial Systems (UAS)

technology for agricultural chemical spraying in the 1980s [11], followed by crop dusting in the 1990s. By 2001, approximately 1,220 units of Yamaha unmanned helicopters had been sold and deployed in Japan [12]. Currently, more than 2,000 Yamaha RMAX unmanned helicopters are used annually to spray nearly 2.5 million acres, covering about 40% of the country's rice paddies [12]. In comparison, the United States has lagged behind Japan in adopting UAVs for agricultural applications, largely due to complex privacy regulations and legal restrictions.

## Current Applications

Although the use of UAVs in agriculture has been steadily increasing worldwide, growth is still constrained by technical challenges that must be addressed. Among the various applications, stress detection and quantification have received the greatest attention due to their potential in mitigating crop losses and improving yields. UAVs are now widely explored for monitoring plant stresses such as drought, diseases, nutrient deficiencies, pests, and weeds.

Crop monitoring for insects, nutrition, diseases, water stress, and overall plant health remains central to precision agriculture. Traditionally, such monitoring was conducted through ground-based surveys or manned aerial observations. However, these methods are limited by high operational costs and restricted coverage. While light aircraft can provide high-resolution imagery at lower costs than satellite platforms, they remain relatively expensive per acre. Small UAVs, on the other hand, enable the acquisition of temporal and spatial data at centimeter-level resolution and can repeatedly fly the same routes and altitudes, ensuring consistency in crop surveillance. Moreover, UAV-based image acquisition is less affected by cloud cover, making data collection more reliable.

## Challenges and Limitations

Despite their promise, UAVs in agriculture face several challenges. Technical barriers include constraints on payload capacity, flight time, hardware durability, and integration of advanced sensors. Legal and regulatory issues—particularly concerning privacy and safety—pose additional hurdles, especially in countries like the United States. Furthermore, the large datasets generated by UAV imaging require sophisticated data processing and interpretation tools, which can be resource-intensive for farmers.

## Objective of the Review

In this context, the objective of this article is to provide a comprehensive overview of UAV applications in agriculture. The review emphasizes plant stress monitoring and precision agricultural practices while also summarizing the major technologies, applications, and challenges that must be addressed for widespread adoption.

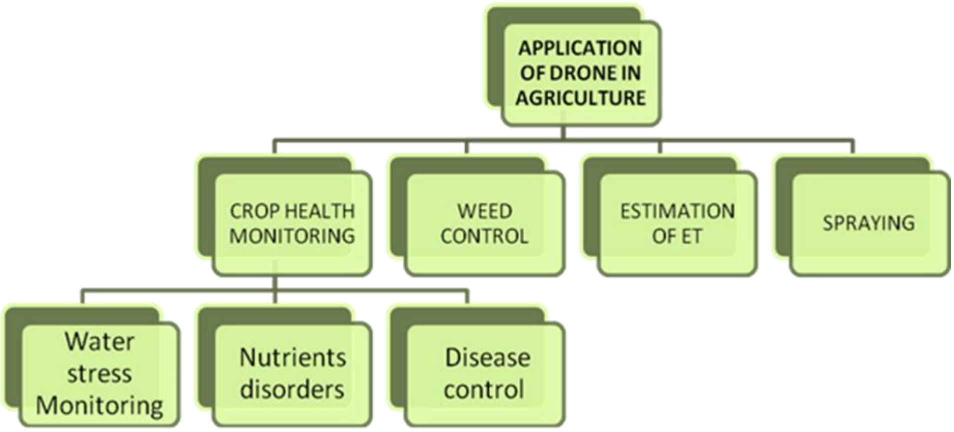


**Fig 1:** Applications of drones in agriculture, including crop health monitoring, weed control, evapotranspiration estimation, and spraying.

## Crop Health Monitoring

Drones have emerged as an efficient tool for monitoring crop conditions throughout the growing season, enabling timely and need-based interventions. By using different types of sensors—such as visible, near-infrared (NIR), and thermal infrared—multispectral indices can be derived from reflectance patterns at varying wavelengths. These indices are valuable for assessing crop conditions related to water stress, nutrient deficiencies, insect-pest attacks, and diseases. Importantly, drone-mounted sensors can detect early signs of stress even before visible symptoms appear, thereby functioning as an early warning system that allows farmers to apply remedial measures in time.

Unmanned Aerial Vehicles (UAVs) are capable of covering several hectares in a single flight while capturing high-resolution data. Equipped with thermal and multispectral cameras [14], drones can record vegetation canopy reflectance. These cameras, mounted on quadcopters, capture images at regular intervals and transmit data to the ground station through telemetry. The data are then processed using vegetation indices, the most common of which is the Normalized Difference Vegetation Index (NDVI) [15]:

$$NDVI = \frac{RNIR - RRED}{RNIR + RRED}$$

NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}}

$$NDVI = \frac{RNIR + RRED}{RNIR - RRED}$$

Where:

- RNIRR_{NIR}RNIR = Reflectance in the near-infrared band
- RREDR_{RED}RRED = Reflectance in the red band

NDVI is a simple yet powerful metric for evaluating green vegetation health. Healthy crops with high chlorophyll content strongly reflect NIR radiation (around 750 nm) while absorbing red and blue wavelengths. NDVI values range from -1 to +1, with values near zero indicating little or no vegetation, and

values between +0.8 and +0.9 signifying dense, healthy green vegetation [12].
By interpreting NDVI maps, farmers can easily identify stressed areas within a field and precisely target interventions such as pesticide or nutrient application. This reduces the need for manual crop scouting, saving both time and labor. Moreover, drones can efficiently monitor horticultural crops, tall plants, and trees in regions that are otherwise difficult to access, such as mountainous or remote areas. By enabling rapid detection and timely action, this technology significantly reduces yield losses and enhances overall farm productivity.

**Water Stress Monitoring**

Characterizing water stress in crops is a complex task, as drought effects are influenced by multiple interacting factors [16]. Thermal imaging is commonly used for water stress assessment; however, it often relies on subtle temperature variations, making thresholds and regression models derived under one condition less applicable under others. For instance, even under identical environmental conditions, different crop genotypes may exhibit distinct canopy temperatures due to variations in stomatal conductance and transpiration rates [17, 18, 19].
Researchers have employed a variety of sensors and indices to identify and quantify water stress

- **Spectral Indices**

Multispectral or hyperspectral imagery is widely used to compute vegetation indices such as NDVI and GNDVI, which highlight crop properties related to water status [16, 20]. The Photochemical Reflectance Index (PRI), sensitive to carotenoid pigment changes, has also been used for detecting stress responses [17, 20, 21].

- **Thermal Infrared Imaging**

Thermal infrared data provide canopy temperature measurements, either directly [16, 22] or indirectly through derived indices. The Crop Water Stress Index (CWSI), for example, normalizes the difference between canopy and air temperature (Tc - Ta) using vapor pressure deficit (VPD) [18, 19, 21]. Related parameters such as the Non-Water Stress Baseline (NWSB) have also been applied to evaluate crop stress levels [23].

- **Hybrid and Alternative Approaches**

RGB imagery, though less commonly used, has been integrated with multispectral or thermal data to derive hybrid indices such as the Water Deficit Index (WDI) [24]. Additionally, chlorophyll fluorescence—calculated from narrow-band multispectral imagery—has been explored sporadically for water stress detection.
The underlying principle in most approaches is that water stress reduces stomatal conductance, leading to less transpirational cooling and consequently higher canopy temperatures [16, 24]. This physiological response can be effectively detected by UAV-mounted sensors, enabling precise and timely assessment of crop water status.

**Nutrient Status and Deficiency Monitoring**

Adequate levels of essential nutrients are critical for healthy plant growth and optimal yield. Nitrogen supports vigorous vegetative growth, phosphorus is essential for root and stem development, and potassium enhances disease resistance while improving crop quality. When soils are deficient in these nutrients, plants experience stress and reduced productivity.
UAV-based imaging offers a promising approach for early detection of nutrient deficiencies. Multispectral and near-infrared (NIR) imagery enable the calculation of vegetation indices (e.g., NDVI), which can identify nutrient-deficient zones before symptoms become visible to the naked eye. These management zones can then be targeted with site-specific interventions, minimizing yield losses and improving resource efficiency.
Traditionally, nutrient status has been assessed through visual inspection using plant color guides, which lack quantitative precision [26], or through laboratory-based leaf analysis, which, while accurate, is time-consuming and resource-intensive [27]. Alternative approaches include chlorophyll meters such as the SPAD (Soil-Plant Analysis Development) meter for nitrogen estimation [28]. However, SPAD-based assessments are labor-intensive and not always reliable across crops and conditions [29, 30].
To overcome these limitations, UAVs equipped with advanced sensors have been increasingly explored. Among plant nutrients, nitrogen has been the most extensively studied due to its direct relationship with biomass accumulation and yield. Other nutrients such as potassium and sodium have also been investigated [32]. Multispectral imaging remains the predominant method for extracting meaningful indices [33, 34], though RGB [35] and hyperspectral imaging [33] are also widely applied.
Recent studies have also focused on data fusion approaches, combining multispectral, RGB, and thermal imaging for more accurate nutrient monitoring [35]. Vegetation indices (VI) are typically extracted from images and correlated with nutrient content using regression models, most often linear. Less common approaches involve using average reflectance spectra [32], specific spectral bands [34], color features [36], or principal component analysis (PCA) [37]. Hyperspectral imagery is generally preferred for these advanced analyses, while RGB imagery is used for color-based assessments.

**Disease Monitoring**

Crop diseases—classified broadly as fungal, bacterial, or viral—can cause severe yield losses if not detected and managed in time. Early detection is therefore critical for implementing effective control strategies. UAVs equipped with infrared cameras can capture detailed images of plant canopies, revealing internal physiological changes that may not be visible to the naked eye [38]. By detecting infections in their initial stages, farmers can apply preventive measures such as targeted treatment or removal of infected plants before the disease spreads to neighboring crops.
Image-based tools play an increasingly important role in plant disease detection, particularly in situations where human visual assessments are unreliable, inconsistent, or infeasible across large areas [39]. UAVs provide extended coverage, enabling rapid surveillance of vast fields and facilitating the identification of disease hotspots.
Different imaging technologies have been employed for disease monitoring:

- RGB imagery is widely used due to its simplicity, affordability, and ease of interpretation [39, 40].
- Multispectral imagery provides additional insights by capturing reflectance data across bands sensitive to plant stress [41, 42].
- Hyperspectral imagery offers fine spectral resolution, enabling the detection of subtle physiological changes linked to specific pathogens [43, 44].
- Thermal imagery is particularly useful for identifying secondary stress factors, such as water stress, which can be associated with disease progression [43, 44].

## Weed Control

Weeds are undesirable plants that compete with crops for essential resources such as water, nutrients, light, and space, often leading to significant yield losses. In India, yield reductions due to weeds have been reported as: Rice (10-100%), Wheat (10-60%), Maize (30-40%), Sugarcane (25-50%), Vegetables (30-40%), Jute (30-70%), and Potato (20-30%) [45].

Traditionally, weed management has relied heavily on herbicide applications or manual uprooting after crop emergence. In conventional practice, uniform amounts of herbicides are sprayed across entire fields, regardless of weed distribution. This indiscriminate application not only increases production costs but also contributes to the development of herbicide-resistant weed populations and adversely impacts crop health and yield. Moreover, excessive herbicide use poses serious environmental threats, including soil and water pollution.

Recent advances in UAV technology offer site-specific weed management solutions. By generating high-resolution weed cover maps, drones enable precise herbicide applications only in infested areas, thus reducing chemical usage and minimizing environmental hazards. Different sensing technologies have been successfully employed for weed detection:

- Hyperspectral imagery has been used to distinguish spectral signatures of weeds with varying resistance to herbicides such as glyphosate 46].
- RGB sensors have proven effective for classifying different weed species [47].
- Drone-based hyperspectral sensors can monitor weeds by analyzing canopy chlorophyll content and leaf density [48

Agro-drones further enhance weed control by enabling efficient pre-emergence and post-emergence herbicide spraying. They are capable of operating under diverse field conditions, including muddy soils, weed infestations, insect presence, as well as in sunny or drizzling weather. Compared to conventional methods, UAV-based spraying optimizes herbicide usage, improves efficiency, and reduces labor dependency. Additionally, drones are lightweight, portable, easy to maintain, and operated remotely—making them safer for farm workers' health.

## Spraying

Indian agriculture requires both production and protection inputs to achieve high productivity. Fertilizers and pesticides are frequently used to promote crop growth and protect against insect-pests. Drones offer a modern solution for spraying chemicals such as fertilizers, pesticides, and micronutrients, enabling site-specific application based on crop health and field variability. The spraying rate can be adjusted according to crop conditions or the severity of pest and disease attack, thereby improving efficiency and sustainability.

Integration of UAVs with spraying systems provides an advanced platform for pest management and vector control, especially in large crop fields. For extensive spraying, heavy-lift UAVs are required [52, 53], whereas quadcopters (QCs) offer a low-cost and lightweight option suitable for both indoor and outdoor crops [54]. These systems can operate autonomously, and communication with android devices via Bluetooth enables real-time control. PWM controllers improve spraying uniformity and efficiency in pesticide applications [55, 56].

Innovative designs include a blimp-integrated quadcopter aerial automated pesticide sprayer (AAPS) for GPS-based spraying at low altitudes [57] and the cost-effective UAV system "Freyr," controlled via mobile applications [58]. Field and laboratory studies have evaluated UAV-mounted sprayers in terms of discharge rate, pressure, spray uniformity, droplet size, and deposition efficiency [59]. To minimize wastage, electrostatic spraying technology has been combined with UAV platforms, significantly enhancing droplet adhesion on plant surfaces [60].

The human health risks from conventional spraying methods are severe—WHO estimates over one million pesticide poisoning cases annually, with more than 100,000 deaths, particularly in developing countries [61]. UAV-based spraying reduces direct human exposure, preventing pesticide poisoning and associated neurological disorders. Compared to tractors or manual methods, UAVs can spray chemicals faster, with greater precision and less environmental impact [62, 63].

Recent studies have investigated the performance of UAV spraying systems under different heights, droplet concentrations, and wind conditions for controlling diseases such as powdery mildew in wheat [64]. UAV spraying enhances chemical efficiency while reducing soil and water pollution, thus contributing to sustainable agriculture.

Fertilizers—including macronutrients (N, P, K) and micronutrients (S, Mg, Zn)—are conventionally applied using ground-based equipment (tractors, pressurized irrigation) [65] or manned aircraft [66]. However, these methods often use uniform application rates, disregarding field variability. UAVs equipped with multispectral, thermal, and hyperspectral sensors can estimate crop nutrient status across entire fields, providing valuable insights for variable-rate fertilizer recommendations [67-71]. Moreover, UAV-mounted systems with accelerometer and gyroscope sensors have demonstrated the ability to improve spraying accuracy, reduce time, save labor, and lower input costs—offering a promising step toward precision, safe, and sustainable crop management.

**Table 1:** Applications of UAV-based sensors and models in agriculture for monitoring water stress, nutrient disorders, diseases, weeds, evapotranspiration, and precision spraying.

| Application | Sensor/Model Used | Reference(s) |
|---|---|---|
| Water Stress Monitoring | Multispectral/Hyperspectral sensors - NDVI, GNDVI, PRI | [16, 20, 17, 20, 21] |
| | Thermal infrared sensor - Canopy temperature, Tc-Ta | [27, 28, 29, 30, 33] |
| | RGB sensor - Water Deficit Index (WDI) | [24] |
| Nutrient Disorders | RGB, Multispectral, and Hyperspectral sensors | [33, 34, 35] |
| Diseases Monitoring | RGB sensor | [39, 40] |
| | Multispectral sensor | [41, 42] |
| | Hyperspectral and Thermal sensors | [43, 44] |
| Weeding | Hyperspectral sensor | [46, 48] |
| | RGB sensor | [47] |
| Evapotranspiration | Multispectral and Thermal sensors | [49, 50] |
| Spraying | GPS sensor | [57] |
| | Accelerometer and Gyroscope sensors | [72] |

**Conclusion**

Drones hold immense potential to transform Indian agriculture by enhancing precision, efficiency, and sustainability. With continued technological advancements, the production and adoption of drones are likely to become more economical and farmer-friendly. Their integration into agriculture may also attract modern youth towards farming by reducing drudgery and introducing innovative practices.

Drones provide real-time, high-resolution imagery superior to satellite data, enabling applications such as weed and disease detection, soil property analysis, crop health monitoring, irrigation management, and the development of accurate elevation models. By leveraging these capabilities, farmers can optimize inputs, reduce chemical usage, and improve overall productivity.

Farmers using drones have already reported tangible benefits, including efficient land use, early pest and disease management, improved soil and irrigation practices, and enhanced crop resilience. In the long run, drones are poised to become an integral component of farming systems, empowering farmers to manage resources more effectively while moving towards sustainable agriculture.

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