Revolutionising Agriculture: A Comprehensive Review of Remote Sensing Techniques Utilising Drones

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Abstract— This paper examines the expanding use of remote sensing technology in agriculture, which has been made possible by developments in airplanes, satellites, Unmanned Aerial Vehicles, and ground-based remote sensing methods. It goes over the numerous ways that remote sensing data is being used to boost crop productivity, boost revenue, and safeguard the environment. The paper provides numerous examples of how remote sensing methods and unmanned aerial vehicles have been used to control weed growth, predict agricultural productivity, assess soil nutrient content, and determine plant nutrient requirements. The study also evaluates this technology's current limits and looks into potential future development options.

Index Terms—Remote Sensing, Unmanned Aerial Vehicles, Drones.

I. Introduction

Aerial drones and remote sensing are two related technologies that are used to gather data about the surface and atmosphere of the Earth from a distance.

Unmanned aerial vehicles (UAVs), or aerial drones, are miniature aircraft that may be flown from a distance. They have sensors, cameras, and other tools that allow them to gather information about the surroundings from a bird's eye perspective. UAVs with remote sensing have several uses in agriculture, from crop health monitoring to increasing crop yields and conserving resources. As time passes, the utilization of this technology is becoming more prevalent in farms worldwide. Common use cases for this technology in agriculture include;

Crop health monitoring: Using remote sensing drones, aerial photographs of crops can be taken and processed to spot disease or stress points. The use of pesticides and other chemicals can be decreased by using this information to target particular areas for treatment.

Precision Agriculture: Sensors that assess soil moisture, nutritional levels, and other elements that influence crop growth can be fitted to remote sensing drones. The field may be accurately mapped using this data, and the maps can subsequently be used to direct precision farming techniques like variable-rate irrigation and fertilization.

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Yield Prediction: Using information on plant height, leaf area, and biomass, remote sensing drones can predict crop yields. farmers can utilize this data to guide their decisions on crop marketing and harvesting.

Crop Mapping: Using remote sensing drones, detailed maps of fields may be made, allowing for the identification of regions with high and low productivity. Crop rotations and other management strategies that increase yields can be planned with the help of this knowledge.

II. Types of Unmanned Aerial Vehicles

Although there are many different types of UAV airframes, rotorcraft and fixed-wing aircraft are the most common (Fig 1). Each airframe has particular advantages and disadvantages. Although rotocopter airframes are recognized for their ease of use, flight stability, hover capability, and ability to take off and land vertically, their flight time and coverage area are limited. In-fact flight time is generally only 30 minutes and it covers an area of 60,000m to 80,000m, and this depends on altitude. Fixed-wing UAV airframes, in comparison, may fly for longer periods of time, exceeding the one hour mark. Fixed wings can cover bigger areas, in the range of 10,000m–40,000m. Again area and duration of flight depends on the altitude, and battery storage capacity [1] [2]. The negative side of fixed-wing UAVs is that they do not have hover capability and necessitate a larger takeoff and landing space than rotocopters.

Rotocopters' flight attributes make them well-suited for agricultural research, while the fixed wing is more typical for agricultural production applications. Since blimps, helicopters, and hybrid UAVs (with characteristics of rotocopters and fixed-wings) are not frequently used in agriculture, this review will only address rotocopter and fixed-wing UAV airframes.

Fig. 1. (a) Fixed wing drone and (b) rotorcraft drone

III. Sensors used in Agriculture

Improvements in UAV-based remote sensors are ongoing in terms of resolution, accuracy, user-friendliness, dependability, and affordability. This section of study will review the prevalent imaging sensors and their usage in agricultural settings. The focus is on three primary types of imaging sensors: color, spectral, and thermal cameras which are intended to capture specific portions of the electromagnetic spectrum (ranging from 450 to 15,000 nm) mainly consisting of visible and infrared segments.

A. Color Cameras

Visible light is captured by color cameras, which are among the most commonly used instruments in remote sensing and can gather a variety of valuable agronomic data. Hue, saturation, and intensity are examples of color components that can be extracted and utilized in various applications such as stand count [3], weed detection ([4], and biotic stress detection [5].The images produced by color cameras can also be incorporated into machine learning workflows to automatically classify sets of images based on objects. Color cameras are also capable of capturing high-resolution imagery, with resolutions ranging from around 10 megapixels to over 30 megapixels, which cannot be achieved by other cameras. This enables the creation of highly detailed digital crop height models and can enhance the accuracy of machine-assisted classification software. Raw color imagery only records a single-color value per pixel, so color imagery goes through a process called demosaicing to calculate missing pixel color values. [6]

B. Multispectral and Hyperspectral Cameras

Multispectral and hyperspectral cameras are used to capture various segments of the electromagnetic spectrum emitted by crop tissue, including visible, near infrared, and shortwave infrared. (Fig 2)

Fig. 2. Sentera AGX 710 dual sensor camera used in agriculture.

Spectral cameras can capture visible electromagnetic spectrum segments, as well as the non-visible infrared regions. Multispectral cameras, on the other hand, are specifically designed to capture multiple, but coarse, bands of the electromagnetic spectrum, typically ranging from 3 to 10. Meanwhile, hyperspectral cameras are similar to multispectral cameras, but they capture contiguous portions of the electromagnetic spectrum that can comprise hundreds or thousands of narrow wavelength bands.

Despite the enhanced insights that can be gained from a broader range of spectral indices produced by longer wavelengths, the associated costs are typically much higher and often necessitate the use of proprietary software. Spectral cameras are commonly utilized for generating spectral indices, which involve using algebraic expressions to analyze discrete wavelengths within the electromagnetic spectrum. The normalized difference vegetation index (NDVI), which was introduced by Rouse, Haas, Schell, and Deering in 1973 [7] and as shown in equation 1, is the most frequently used spectral index.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

While the normalized difference vegetation index (NDVI) has gained popularity as one of the primary spectral indices for assessing the health and vitality of vegetation there are several other spectral indices that have been tailored for specific applications (as outlined in Table 1).

TABLE I: COMMON SPECTRAL INDICES

Spectral index	Equation	Use	Source
Difference Vegetation Index (DVI)	DVI = NIR − Red	Differentiate soil and plant	Tucker (1979) [8]
Green Chlorophyll Index (GCI)	GCI = ρNIR ρGreen − 1	Estimate content of chlorophyll	Gitelson, Gritz, and Merzlyak (2003) [9]
Green Difference Vegetation Index (GDVI)	GDVI = NIR − Green	Predict corn nitrogen requirements	Sripada et al. (2005) [10]
Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = NIR − Green NIR + Green	Measure the healthiness of green vegetation	Gitelson and Merzlyak (1998) [11]
Normalized Difference Vegetation Index (NDVI)	NDVI = NIR − Red NIR + Red	Measure of healthy, green vegetation	Rouse et al. (1973) [7]
Red Edge Normalized Difference Vegetation Index (RENDVI)	RENDVI = NIR − Red Edge NIR + Red Edge	NDVI Variant capitalizes on the sensitivity of the vegetation red edge	Gitelson (1994) [12]
Soil Adjusted Vegetation Index (SAVI)	SAVI = 1.5(NIR − Red) NIR + Red+0.5	NDVI Variant suppresses the effects of soil pixels	Huete (1988) [13]
Visible Atmospherically Resistant Index (VARI)	VARI = Green − Red Green + Red−Blue	Measure vegetation density from color camera	Gitelson et al. (2002) [14]

IV. The use of Aerial Drones for Precision Agriculture

Past scientific studies have contributed significantly to agriculture by providing farmers with valuable information and tips on how to improve crop yields, reduce costs, and minimize environmental impact. The following are some concrete examples of how these studies have influenced agriculture and UAV remote sensing:

Logging Farming Activity and Trends.: Intensive farming has a number of detrimental effects on the environment. This technique harms the environment by introducing large amounts of nitrogen and phosphorus to terrestrial ecosystems. Vitousek, Mooney, Lubchenco and Melillo discussed this in their study [15]. Another essential logging should be done on the use of fertilizer. Excessive fertilizer use can also contribute to pollution, and not using enough fertilizer to make up for the nitrogen and phosphorus lost during heavy cropping can degrade the fertility of the soil. In addition, agricultural chemicals that contaminate neighboring water sources cause water pollution and the decline of ecosystems that depend on water. The threat posed by widespread soil deterioration in Europe to soil production is significant [16].

The use of software and AI: Typical modern used algorithms include the use of AI for specific trend analysis, Typical application could be counting, such as tree counting in orchards, fruit tree flower and fruit counts. Counting could also be used for crops. Previous studies have been limited to straight and uniform rows, whereas crops with unpredictable patterns or overlapping plants present research challenges that require further study. To improve accuracy, hyperspectral cameras or LiDAR can be used, although these methods may not be practical due to high costs and the extensive skills which are required by the drone pilots [17]

Farming trends for Health: Conducting a thorough farm health assessment is critical in identifying fungal and bacterial diseases that may affect crops. By utilizing cutting-edge UAV technology and scanning crops with both visible and near-infrared light, farmers can detect any spatial and temporal reflectance variations that may indicate poor farm health. This early detection allows for swift intervention to save the entire farm, enhancing the plant's ability to overcome disease. Furthermore, in the unfortunate event of crop failure, the use of UAV technology can help farmers document losses more efficiently, facilitating insurance claims. [17]

Pest in crops: In recent studies, researchers have investigated the combination of UAVs, remote sensing, and machine learning techniques as a promising solution to address pest problems in farmlands. One successful study, conducted by Jianwei ,Tianjie , Changchun and Jiangqun [18] in the Baiyangdian agricultural zone during the growth season, highlighted how the benefits of UAV over traditional methods to monitor pests, and use this technology for pests reduction .

Phenotyping: As the projected midcentury global population grows by an additional 2.3 billion people, demands for food, feed, fiber, and fuel are expected to increase [19]. To meet this demand, precision technologies such as UAV and remote sensors can be used for crop improvement through genetics and plant breeding, as well as for gathering phenotypic information needed for making management and breeding decisions to optimize agricultural production [20]. Agricultural researchers and plant breeders can gather phenotypic data quickly, efficiently, and nondestructively through UAV-based remote sensing [21]. For instance, UAV-based color sensors can capture diverse data for estimating leaf color, plant height, lodging, canopy cover, analyse flower colours and type. Spectral sensors, on the other hand, can estimate indirect leaf nitrogen content, yield, leaf area index, leaf chlorophyll content, and plant biomass. Additionally, thermal sensors can capture data for estimating canopy temperature, stomatal conductance, water use efficiency, and water potentials of plants.

The timing of sensing is crucial for accurate phenotyping estimates, and typically, accuracy improves as crops mature. To estimate crop height, a digital crop model is produced by finding the difference between the surface model and terrain model [22] [23]. However, to capture the complex surface intricacies of crops, only high-resolution cameras with 10 megapixel resolution or more should be used, as low-resolution cameras, which are less than 3 megapixel may not be sufficient. Ground control points and the "Scale Constraint" feature available in some imagery processing software can also improve crop height estimations. To prevent image blur and moving plants that can decrease estimation accuracy, sensing should be avoided on windy days. The reference for a windy day is if the wind reaches the 16kph magnitude or more.

To utilize UAV technology for disease resistance phenotyping, researchers have generally relied on color and spectral cameras to capture data [24] [25]. By analyzing pixel color ratios, spectral indices, and using machine learning techniques, disease severity ratings can be obtained with varying degrees of accuracy. Tissue coloration has also been used to examine phenotyping characteristics such as tolerance to iron deficiency chlorosis [26]. In addition, the use of UAV technology to gather high-throughput phenotyping data for genome-wide association studies (GWAS) is promising for improving breeding programs. For instance, NDVI generated from UAV-captured data was used by [27] to identify quantitative trait loci (QTL) associated with drought adaptive traits in a panel of durum wheat (Triticum turgidum L.) that accounted for 89.6% of the phenotypic variance.

Predict Crop Yields: Remote sensing has been utilized to predict crop yields by relying mainly on statistical and empirical correlations between vegetation indices and yield, as stated in studies conducted by Thenkabail [28] and Casa and Jones [29]. Crop yield prediction is very important in different sectors, including government agencies for better land and supply plan, commodity traders for attracting more investment, and producers to prepare for harvest, storage, transportation, and marketing activities. The timely availability of this information minimizes economic risk, resulting in improved efficiency and higher return on investments for all parties.

Together with yield prediction, as Rembold, Atzberger, Savin, and Rojas' [30] highlighted, it is also important to assess the quality of crops. Similar to crop yields, quality might be used from regional suppliers, to plan with delivery. Such data could also be used to estimates the cycle duration, harvest timing, storage needs, and financial planning, according to Horie, Yajima, and Nakagawa [31]and Raun et al.'s [32] Yield and quality assessments have traditionally relied on historical yield data, trends and seasonal conditions,. However, crop genetics, weather, soil, and management practices can influence the final crop yield and quality, making them unpredictable. Thus with the use of UAV-based technologies, such quality assessments could be used with machine learning. Mekonnen, Namuduri, Burton, Sarwat, and Bhansali's 2020 research [33] discussed this topic and explained how drone imagery can enhance the accuracy of assessments and potentially eliminate the need for ground-based surveys, according to

When it comes to crop yield quality assessment, timing is critical, since accuracy generally improves as the crop progresses through its lifecycle, [34] [35]. Multiple studies showed that the remote sensing indices listed in table 1 are essential for accurately estimating yields. While Ostos-Garrido, De Castro, Torres-Sánchez, Pistón, and Peña [36] found that the GNDVI during anthesis and full crop development produced more accurate biomass estimates than those obtained earlier, Wahab, Hall, and Jirström [37] reported that GNDVI produced higher accuracy yield estimates early in a crop's lifecycle. As such, selecting appropriate parameters such as spectral indices or color components is critical to the usefulness and accuracy of crop yield and quality estimations. Hyperspectral cameras were found to have potential value in these assessments, as they can capture spectral ranges far beyond those of simpler multispectral cameras .One of these studies was conducted on soybean by Zhang, Zhang, Niu, and Han's [38]. Other studies showed that by incorporating 3D characterizations such as crop height or volume derived from LiDAR or high-resolution color cameras with conventional 2D data may also improve the accuracy of these estimates, [39]. Additionally, combining plant height and NDVI has been shown to improve biomass estimation accuracy [40]

V. CURRENT LIMITATIONS OF AUVS

As highlighted in this literature review, the UAV technology has been successfully deployed in a wide spectrum of agricultural applications for multiple uses, however there are still limitations which need to be addressed.

1) The technical complexity of UAVs contributes to the perception that the technology is expensive. Costs associated with deployment, integration, agriculture usage and training can be high, and not affordable to the average farmer as discussed in [17].

2) The regulation and licensing of UAVs is still uncertain as there is currently a lack of clear guidelines. Regulations and laws in some places are totally different than others. Aviation laws are often used as a loose framework but they do not perfectly align with the use of UAVs. To address this issue, there is a need to develop legislation specifically tailored to regulate the various possibilities and applications of UAVs. Several countries including the USA, and countries in the EU [17] have taken the lead in this effort by creating guidelines that dictate where UAVs can be flown and how they can be used. However, many other countries still lag in this area.

Another current bottleneck in advancing UAV-based precision agriculture lies in the time, and the effort which is required in data collection and to process the data to make it more farmer friendly data [17] If such UAV data could be captured and processed in-field, it would eliminate the need for off-site processing and delivery. With long-term technological improvements, UAV onboard computing will eventually enable autonomous real-time decision making, allowing tasks such as spraying to be carried out without human interaction. However as to date farmers are in need to this all themselves, or otherwise to hire n expert in this area [17] The ideal situation is that UAV automation stations will conduct preprogrammed flights, collect data, transmit it for cloud processing, and return to a charging bay to be ready for the next mission. This data will be easily accessible to users and farmers, without any time investment. Finally, UAV data products will be cloud processed and wirelessly downloaded to tractors and field implements to carry out prescriptions. Obviously, such scenario is still not available today.

3) Passive remote sensors can experience data degradation due to inconsistent lighting conditions, such as cloud movements. To address this issue, approaches could include creating unmanned aerial vehicle-based active spectral sensors or improving software algorithms to account for and correct for these inconsistencies. Furthermore, technological advancements could enable wider use of cooled thermal cameras, to increase the data collection accuracies. The cost of cameras is significantly high as well [17], and if such cost is reduced, this would allow for more widespread use, and will enable more farmers to capture data.

VI. CONCLUSION

In conclusion, the highlighted literature sheds light on how UAVs have the potential to transform the agriculture industry practices by enabling precision agriculture and reducing the environmental impact. Moreover, drones equipped with various sensors, such as cameras, multispectral and thermal sensors, can provide farmers with valuable data on crop health, nutrient levels, and water usage, thus helping farmers to be more efficient with the application of fertilizers, pesticides, and irrigation.

Studies also showed that UAVs can help farmers reduce costs, increase yield, and get more detailed information on crop health, and detect problematic areas on time and take corrective action before significant damage occurs.

Despite this, there are still challenges to overcome in implementing UAVs in agriculture. These include technical-cost challenges, such as developing reliable and cost-effective plans to use UAVs. There are also challenges to get farmers to train as drone operators and get certified as pilots, which require them to learn about the laws and regulations which regulate the UAV sector.

Future research should focus on how to address these challenges and make drone more farmer centric, which will ultimately lead to more benefits for farmers, consumers, and the environment.

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