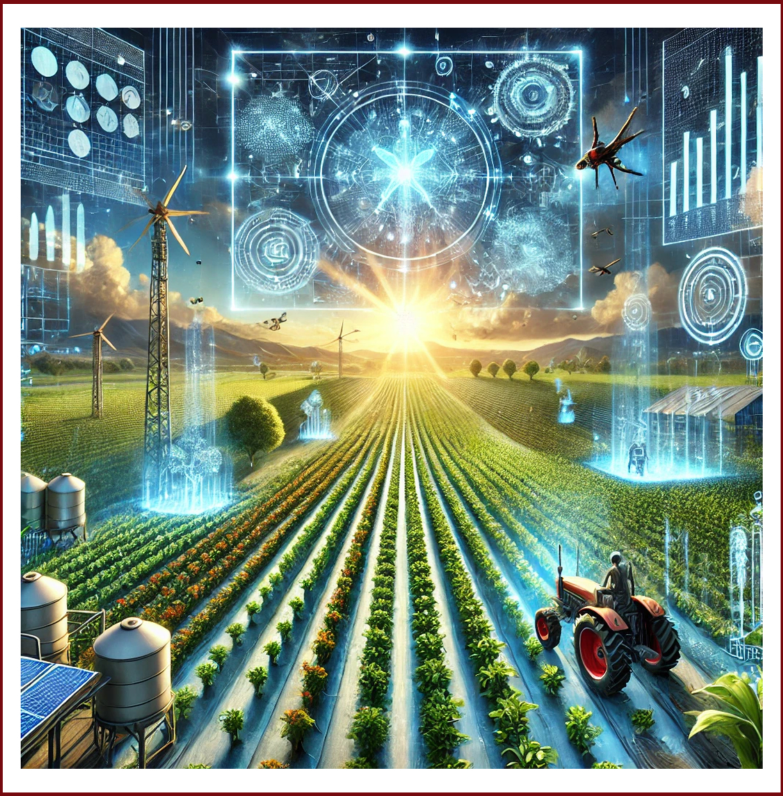

AGRICULTURE, FOREST AND AQUATIC SCIENCES IN THEORY AND PRACTICE

Editörler

Assoc. Prof. Dr. Vedat ÇAVUŞ

Asst. Prof. Dr. Senem GÜNEŞ ŞEN

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Chapter 11

The Potential Use Of Remote Sensing Technologies And Unmanned Aerial Vehicles (UAVs) In Agricultural Fields

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Introduction

Chronic hunger impacts 815 million individuals globally. Asia houses 64% of the global population suffering from hunger. Research indicates that to satisfy the food requirements of a projected global population exceeding 9 billion by 2050, current production must increase by 50% (FAO, 2018; Sylvester, 2018). The agriculture sector must address the impacts of climate change, with diminishing production regions and clean natural resources, to meet these demands. Addressing these difficulties necessitates the swift analysis of data gathered from extensive regions and the immediate transmission of information in agricultural production zones, together with the execution of critical interventions.

Advancements in information and communication technology are increasingly vital in addressing the myriad challenges confronting agriculture. The attainment of the United Nations Sustainable Development Goals also encompasses information and communication technologies (FAO 2018). Agricultural production involves several duties such as tillage, planting, sowing, irrigation, fertilization, spraying, and harvesting. It is vital to monitor these acts. Unlike traditional methods, technical innovations, especially in the aviation sector and diverse sensors and remote sensing technologies, have enabled the implementation of innovative strategies in agriculture.

Plant monitoring studies provide decision-makers with fast access to essential information for agricultural applications. Decision makers in the field are significantly aided in assessing the quantity, timing, and geographical area of agricultural applications by the immediate availability of accurate information. Making appropriate decisions aids in the conservation of natural resources such as soil and water, while also reducing production costs.

In the 1980s, site-specific management, known as precision agriculture and linked to the utilization of contemporary technologies in land management, began to emerge. The basic purpose of precision agriculture is to optimize inputs such as fuel, fertilizer, and pesticides according to local plant and soil conditions (Lukas et al. 2016).

In precision agriculture, the paramount variables to consider are the velocity and precision of situational assessment, together with the implementation of suitable interventions and applications. It is well acknowledged that information-collection methods in conventional agricultural regions are time-consuming, expensive, and location-specific. At now, remote sensing technology is being advanced to facilitate data collection for researchers and cultivators in agricultural sectors. With technological advancements, sensors have diminished in size and cost, enabling their installation on unmanned aerial vehicles (UAVs) that were formerly deployed on satellite platforms. This technical innovation enables the acquisition of data with enhanced temporal and geographical resolution. According to the collected data, UAVs have become extensively employed in agricultural regions for activities such as fertilization, spraying, and restricted irrigation, as well as for photography.

This study encompasses research on UAV uses in agriculture, fulfilling many roles both nationally and globally. The objective is to enhance the existing literature by meticulously analyzing the historical and modern uses of UAVs in agriculture.

UAVs and Sensors

Recently, there has been significant interest in employing remote sensing technologies to collect data on the physiological condition and biophysical characteristics of plants. Various studies, encompassing plant water stress assessment, vitality evaluation, biomass calculation, and disease surveillance, can profit from the novel UAV and remote sensing technologies. Multispectral, hyperspectral, and thermal images have proven to be more advantageous due to their superior spectral compatibility, despite the extensive use of visible RGB images in various research investigations (Qin et al. 2013, Park and Lu 2015; Pádua et al. 2017). In plant monitoring studies, vegetation indices obtained from diverse ratios of many multispectral and hyperspectral camera bands provide very accurate data transmission (Sener et al. 2018).

Numerous studies have demonstrated the significant potential of hyperspectral sensors in identifying environmental stressors or plant diseases that affect the biophysical (Aasen et al., 2014; Gnyp et al., 2013) and biochemical (Li et al., 2010; Yu et al., 2013) characteristics of agricultural plants and vegetation. The primary challenge of employing hyperspectral cameras on UAVs was their excessive size and weight. Compact, lightweight cameras built for unmanned aerial vehicles (UAVs) have addressed this problem.

In drought conditions, plants cannot absorb sufficient water for transpiration, resulting in elevated temperatures of the leaves and crown. Thermal bands are utilized to monitor plant water stress, whereas RGB and infrared bands are mostly employed to evaluate plant development. Figure 1 illustrates a standard vegetation spectral reflectance curve.

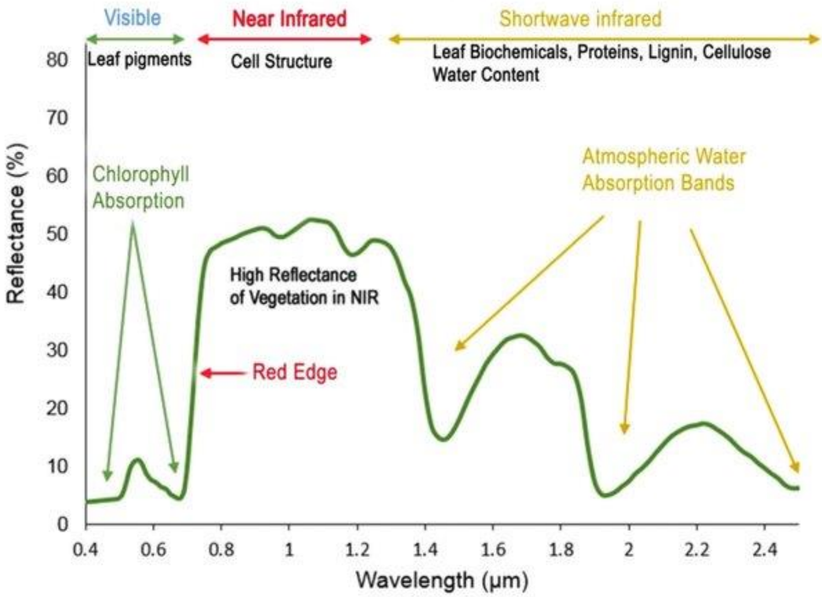

Figure 1. Spectral reflectance of vegetation (Roman and Ursu, 2016)

Four separate types of sensors are deployed in every UAV application for precision agriculture research. Table 1 presents data regarding the utility of these sensors in several application sectors (Maes and Steppe 2019).

Table 1. Analysis of Applications and Appropriateness of Various Sensors

Application		Type of sensor/camera			
		RGB	Multispectral (broad band)	Hyperspectral (Narrow band)	Thermal
Drought stress	Detection in early stages	--	--	S[b]	HS
	Long-term consequences	--	HS	HS	S
Pathogen detection	Detection in early stages	--	--	HS	HS
	Severity of infection	HS	HS	HS	S
Weed detection	Spectral discrimination	--	S	HS	--
	Object based	HS	HS	--	--
Nutrient detection		S	HS	HS	S
Growth vigor	Growth stage	HS	--	--	--
	Canopy height and biomass	HS	HS	--	--
	Lodging	HS	--	--	S
Yield prediction		S	HS	--	--

[a] Abbreviations: HS, Highly suited; S, Suited

[b] Calculation of sun-induced florescence from hyperspectral data

Agricultural practices

Advancements in remote sensing technology enable UAVs to provide very accurate data across extensive areas, especially in plant monitoring and assessment studies. UAV-based remote sensing technologies provide significant advantages for enhancing agricultural productivity. Agricultural output can be enhanced by integrating sensor data with real-time information provided across the field parcel. As per FAO (2018), UAVs can provide valuable insights on various topics, such as soil health, plant diseases, fertilizer application, irrigation scheduling, yield estimation, and weather forecasts. This section will explore the applications of UAV-based remote sensing technology in agriculture, emphasizing yield estimation, biomass assessment, soil moisture and water stress analysis, as well as disease and insect management.

Crop Yield

Crop yield is often determined using estimates from remote sensing or direct measurement. Field measuring strategies for providing sufficient inventory data across extensive areas are costly and need a substantial workforce. In this research, estimation strategies utilizing remote sensing markedly enhance efficiency. Remote sensing has significantly enhanced crop monitoring and production assessment.

Upon reviewing the UAV-based yield estimation research, it is evident that they focus on sorghum, barley (Roosjen et al. 2016), corn, rice, and wheat (Schirrmann et al. 2016).

Research employing RGB images of plant height and canopy cover by UAV (Chu et al. 2016), vegetation indices (Gracia-Romero et al. 2017), or multispectral images (Zhou et al. 2017) has achieved a reasonable degree of accuracy in yield estimation. In 2010, Swain et al. assessed rice yield and biomass utilizing a multispectral camera and an unmanned aerial vehicle (UAV).

Maes and Steppe (2019) indicate that yield estimation strategies have focused on plant growth models utilizing empirical regression models derived from UAVs. The GRAMI growth model was successfully employed for rice yield estimation using UAV-based data, as reported by Kim et al. (2017). Moreover, LIDAR technology provides high-resolution elevation data, which can be employed in yield estimates, as noted by Xu et al. (2020).

Biomass And Nutrient

Monitoring plant biomass development yields critical information for agricultural management. Lukas et al. (2016) utilized UAV and LANDSAT satellite imagery to analyze various characteristics during the growth phase of winter wheat plants. Upon conclusion of the study, UAV-derived data exhibited superior precision relative to satellite data, indicating that wheat plants can be utilized for specialized plant management and variable-rate fertilizer applications in specific regions.

Figure 2. Biomass measurement studies in paddy with UAV

Utilizing RGB-based imagery to monitor cereal crops can provide comprehensive insights (Schirrmann et al. 2016; Du and Noguchi 2017). Dillen et al. (2016) reported that UAV-based RGB photography yielded satisfactory outcomes for orchards, whereas Watanabe et al. (2017) indicated that these cameras effectively estimated plant heights for cereals.

Zarco Tejada et al. (2012) assert that vegetation indices are commonly employed to assess plant water stress, health condition, metabolic processes, biomass, and yield. In the analysis of plant phenological development, various vegetation indices are utilized, with the NDVI being the most prevalent.

Deng et al. (2018) emphasized the importance of UAV multispectral remote sensing technology in precision agriculture by utilizing multispectral imagery from a multirotor UAV to compare NDVI and reNDVI vegetation indices with field-level SPAD measurements.

Pölönen et al. (2013) utilized a machine learning methodology to assess nitrogen levels and biomass in wheat and barley cultivation areas through the use of a UAV and a hyperspectral camera. The SMART model facilitated atmospheric calibration, whereas radiometric correction was employed for light source calibration.

The quantity of biomass and photosynthesis is generally regarded as an indicator of vitality (Goulet and Morlat 2011). Wine professionals can obtain essential information by generating vigor maps utilizing vegetation indicators like NDVI (Costa-Ferreira et al. 2007). Gnadinger and Schmidhalter (2017) employed remote sensing techniques to ascertain the relationship between plant population and diverse fertilizer applications in relation to plant indices. The study demonstrated the utility of remote sensing in plant development.

Lelong et al.'s 2008 work utilized UAVs to observe wheat plots with high-resolution image processing. The study examined the potential correlation between total nitrogen content and the NDVI, LAI, and GNDVI plant indices. Meng and Cheng (2020) employed UAV flights and an algorithm to improve the resolution of time-series satellite images of cornfields and used these images to assess soil nutrient content. Songyang et al. (2018) assessed the nitrogen content in the leaves of rice plants in China utilizing a UAV and a RapidSCAN CS-45. Gao et al. (2000) assert that the quantity of chlorophyll in aboveground plant biomass is substantial and significantly influences NDVI. In contrast, they asserted that EVI is more effective in connecting with biomass as it directly reflects structural changes in the plant canopy.

Field-based fertilization based on soil and plant N concentration is a crucial component of precision farming techniques. While fertilizing the entire area using the old way costs farm owners a lot of money, it can also pollute soil and water resources. With the use of multispectral and hyperspectral cameras, it is now possible to determine the N content in real time using the spectral reflectance value of plant leaves. According to Maresma et al. (2016) and Hunt et al. (2018), most UAV-conducted research concentrates on using multispectral displays to measure the amount of chlorophyll or nitrogen present. According to Franceschini et al. (2017), vegetation indices and the amount of chlorophyll in potatoes are highly correlated. Lucieer et al. (2014) used a hyperspectral camera-loaded UAV to collect 324 spectral band data between 361 and 961 nm to investigate the validity of the assessment of green biomass in barley and the chlorophyll content in pasture. According to Franceschini et al. (2017), vegetation indices and the amount of chlorophyll in potatoes are highly correlated. Lucieer et al. (2014) used a hyperspectral camera-loaded UAV to collect 324 spectral band data between 361 and 961 nm to investigate the validity of the assessment of green biomass in barley and the chlorophyll content in pasture.

Thermal and infrared sensors, along with light detection and ranging (LIDAR) technologies, have been employed to examine several parameters, including biomass estimation, vegetation canopy height and temperature, and nitrogen and chlorophyll levels (Andujar et al., 2013; Maimaitijiang et al., 2017). Shendryk et al. (2020) utilized LIDAR data and multispectral imagery as inputs for variable nitrogen fertilization in Australian sugarcane fields. Research on this subject remains nascent; specifically, investigations into precision agriculture and variable-rate nitrogen applications are said to be inadequately developed (Maresma et al. 2016).

Sugar beet is mostly employed for sugar production, but it is also utilized for generating renewable bioenergy. Advancements in remote sensing, particularly in LIDAR (Light Detection and Ranging) technology, have facilitated the measurement of the biomass of aboveground vegetation. Xu et al. (2020) employed machine learning to analyze UAV and LIDAR data in China for the estimation of sugar beet output. Among the six methodologies utilized to estimate sugar beet production, the study revealed that Random Forest Regression (RFR) exhibited the highest correlation (R2 = 0.96).

Honkavaara et al. (2012) employed point clouds and hyperspectral reflectance data to develop a novel biomass estimation technique supported by a vector regression machine for UAV-based precision agriculture research. This study aimed to enhance the accuracy of the estimating process through the use of digital elevation modeling, high-resolution imagery, and advanced image analysis. This latest technology was employed to develop a resilient, economical, and locally reproducible remote sensing application.

Soil Moisture and Water Stress

Stomata close and transpiration diminishes because to the temperature increase induced by dryness. UAV-based thermal imagery has been employed in many studies to assess water stress in different plant species for the purpose of monitoring drought effects and irrigation scheduling research.

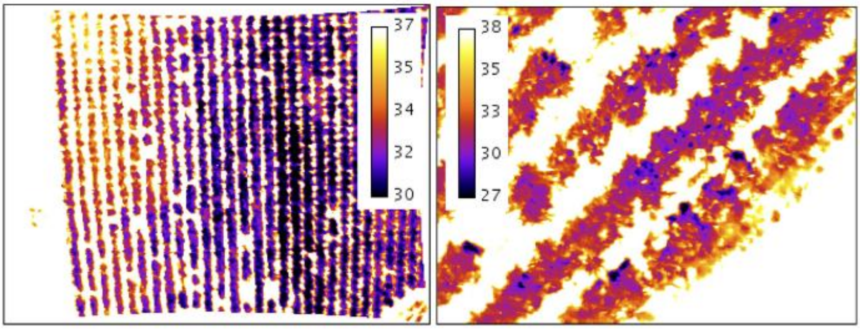

Figure 3. An example of water stress study in orchards using UAV (Zarco-Tejada et al., 2018).

Romero-Trigueros et al. (2017) conducted experiments on citrus water and soil salinity stress using UAVs and multispectral camera pictures. They claimed that the combination of field measurements and remote sensing data produced significant findings.

Gago et al. (2015) assert that the superior spatial and temporal resolution of UAVs significantly enhances water stress management in agriculture. Their review analysis indicates a robust correlation between water stress indicators, such as stomatal conductance (gs) and water potential, and NDVI, TCARI/OSAVI, and PRInorm indicators collected from UAV imagery. They assert that thermal imaging is a remote sensing method commonly utilized as a thermal indication for assessing leaf water stress. Zaman-Allah et al. (2015) endeavored to correlate plant growth parameters with the NDVI plant index they established utilizing data from a multispectral camera. They asserted that the study's remote sensing methodology could detect the different stresses affecting plants.

Diverse growth methodologies, such the leaf area index (LAI) and the normalized difference vegetation index (NDVI), produce valuable insights into the effects of water stress. Remote sensing methodologies can detect water stress in barley genomes (Hoffmann et al. 2016).

Hafızoğlu (2020) utilized drones to amalgamate plant physiology and biochemical research areas and evaluate tolerances to examine the alterations in plants induced by drought. The activity of superoxide dismutase and the relative water content in maize plants exhibited a positive correlation with NDVI data, whereas protein and malondialdehyde levels demonstrated a negative correlation.

Xiangyu et al. (2019) employed images captured by a UAV equipped with a hyperspectral sensor and a machine learning algorithm to assess elevated soil moisture content. Rapid advancements in remote sensing technologies have led to the emergence of thermal and hyperspectral cameras, alongside radar technology, for evaluating soil moisture content (Sener et al. 2019).

Water use is intimately associated with the temperature of the foliage and canopy as assessed by remote sensing methodologies. During water stress, plants exhibit reduced transpiration, closure of stomata, and an increase in temperature. In this connection, Bellvert et al. (2016) utilized thermal cameras to optimize irrigation scheduling, whereas Zarco-Tejada et al. (2008) investigated water content and the assessment of plant water stress. Thermal imaging is optimal for detecting drought stress (Maes and Steppe 2012).

Zarco-Tejada et al. (2012) investigated water levels in lemon trees with PRI data and regulated deficit irrigation methods. They utilized thermal and hyperspectral sensors to detect water stress by analyzing canopy temperatures, brightness, and reflectance spectra.

Numerous attributes inaccessible in RGB images can be acquired with thermal photography. Direct measurement of plant surface temperatures during stress tests may yield erroneous results. Normalized indicators for surface temperatures, such as the Crop Water Stress Index (CWSI), are utilized to prevent this misinterpretation. A 2019 study by Bhandari et al. examined the efficacy of multispectral and hyperspectral cameras in assessing nitrogen and water stress, employing the Water Band Index (WBI) alongside vegetation indices for citrus.

Galioto (2017) stated that drip and pivot irrigation technologies were essential for field agricultural research, despite UAV-supported thermal camera studies yielding significant results in stress assessments in orchards. Furthermore, a negative association exists between soil temperature and moisture content. Soil temperature increases as soil moisture content decreases. Konstantin et al. (2018) and Fengshuai and Arj (2020) assert a robust association between soil moisture content measurements obtained from heat and radar sensors on UAVs and the actual soil moisture levels determined by the gravimetric method. Irrigated plots inside irrigation zones are recognized with thermal cameras (Sener et al. 2019).

Disease And Pest Management

Diseases and insects can swiftly spread throughout a sizable agricultural area, and their harm can significantly impact the local and national economies. Rapid interventions in wide areas are necessary to eliminate such issues, reduce damages, and ensure food safety. In this regard, UAVs and imaging systems are seen as helpful resources, particularly when offering comprehensive details regarding the beginning of illnesses and the regions they impact.

Handheld compressed air sprayers and battery-operated shoulder-mounted sprayers are the primary instruments employed in conventional agriculture for the application of pesticides to crops. The World Health Organization has recorded over one million cases of pesticide-related adverse events during manual spraying, suggesting that the use of such sprayers can significantly harm the environment and human health (Toscano et al., 2024). Unmanned Aerial Vehicles (UAVs), capable of various functionalities, have been employed to address pesticide exposure issues for agricultural equipment and personnel, as opposed to conventional spraying methods (Babaoğlu et al. 2021).

Figure 4. DJI Agras T50 (Team, n.d.)

The International Association of Unmanned Aerial Systems forecasts that 80% of all UAV applications will pertain to agriculture (Radoglou-Grammatikis et al., 2020). Currently, numerous firms have commercially created a wide variety of spraying UAVs, alongside specially customized spraying UAVs. The market clearly indicates that the DJI Agras models are the most favored rotor systems. Over the years, DJI Agras has developed several models with differing capacity, including the T16, T20, T30, T40, and T50. Each model has been designed with a distinct array of technological attributes and functionalities (Team, n.d.).

Large tanks are currently employed for spraying plants, whereas formerly, small tanks were conveyed by helicopter. The initial step in effectively utilizing such research is to employ picture capturing and analysis to ascertain the pesticide concentration in the treated areas. This will avert economic damage and chemical contamination of the entire region (Wen et al. 2019).

Garcia-Ruiz et al. (2013) utilized UAVs to examine citrus fruit disease and health. They conducted research to identify Verticillium wilt, which impedes olive tree growth. The study included thermal and multispectral camera images for early illness detection (Calderón et al. 2013). It was found that eliminating erroneous observations in multispectral imaging allows hyperspectral imaging to detect early-stage disease more effectively. Nonetheless, it is apparent that research employing UAVs to detect fungal diseases via hyperspectral cameras has not been sufficiently conducted (Mahlein, 2016).

Problematic areas were found using NDVI imagery in the study that employed multispectral cameras to detect regions demonstrating stunted plant growth. The flawed regions were subsequently sprayed to address the production problem (Mogili and Deepak, 2018). Uzun et al. (2018) indicate that farmers effectively managed diseases, pests, and weeds with the use of agricultural UAVs, resulting in enhanced success.

Agnihotri (2018) examined the efficacy of thermal and multispectral imagery, supported by machine learning, for pest detection in rice fields. The identification of pathogen-related disorders has been the focus of extensive research. It was said that further study is underway about the application of hyperspectral cameras for disease detection, utilizing wavelengths ranging from 380 to 1020 nm (Thomas et al. 2018; Mahlein et al. 2018; Abdulridha et al. 2020).

Akkamış and Çalışkan (2020) assert that pesticide applications conducted by inadequately trained personnel utilizing agricultural UAVs could provide detrimental impacts. Determining the appropriate pesticide dosage for a certain condition, modifying flight altitude and velocity, utilizing suitable nozzles, and ensuring application by entities with the requisite legal permissions are all essential for the user.

Discussion

UAVs are growing in popularity as inexpensive equipment for monitoring plants and land for in-depth study by management and decision-makers in agricultural sectors. Because RGB, multispectral, thermal, and hyperspectral cameras offer data at varying spatial and spectral resolutions, they are favored for various uses, sizes, and specifications.

Even though remote sensing and UAV technologies appear to be very helpful tools, it is only feasible to comprehend this data by comparing it with data from the ground. One of the most crucial factors in gathering and analyzing data is the researcher's proficiency with the kind of plant and issue under observation. It is crucial to seek assistance from specialists with knowledge of plant, disease, or stress issues to properly examine the data in studies carried out by researchers who lack infrastructure related to the topic of the study and only possess software and hardware expertise.

It has been observed that the reduction in the cost of UAVs and the equipment they require has a favorable impact on the adoption of UAV and remote sensing technologies in agriculture and helps distribute them to end users. It is a truth, nevertheless, that image processing software is not widely utilized outside of the classroom, and memberships are still below what businesses in the modern world would like to have. Since prices are now tied to the nation's economy and the needs of rural areas, it is evident that the only way to promote commercial use is to re-adjust them.

Making these technologies more user-friendly is advantageous for improving the use of UAV and agricultural applications. The contemporary UAV business is still moving quickly in the direction of more practical, user-friendly agricultural vehicles. These studies' primary goal is to assist users in increasing agricultural productivity and cutting expenses.

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