Application of UAV based high-resolution remote sensing for crop monitoring

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Abstract*: Advances in technologies could offer enormous potential for crop monitoring applications, allowing the real-time acquisition of various environmental data. Technology such as high spatio-temporal imagery of unmanned aerial vehicles (UAV's) can be widely used in crop monitoring applications. These technologies are expected to revolutionize the global agriculture practices, by enabling decision-making during the crop cycle days. Such results allow the effective practice of agricultural inputs, aiding precision agriculture pillars, i.e., applying the right practice in the right place, with the right amount and time. However, the actual exploitation of UAV's has not been much strong in smart farming, mainly due to the challenges faced during selecting and deploying relevant technologies, including data acquisition and processing methods. The major problem is that there is still no consistent workflow for the use of UAV's in such areas, as this mechanization is relatively new. In this article, the latest applications of UAV's for crop monitoring are reviewed. It covers the most common applications, the types of UAV's used and then we focused on data acquisition methods and technologies, employing the benefit and drawbacks of each. It also indicates the most popular image processing methods and summarizes the potential application in agricultural operations.

***Keywords*: Precision agriculture, Remote sensing, Unmanned Aerial Vehicle (UAV), Crop monitoring**

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I. INTRODUCTION

After a decade, the past few years have seen a growing interest in investment in the agriculture sector. The number of increased investments aimed to achieve a higher productivity growth rate to meet the global demands. technologies permitting real-time agriculture management [1]. The UAV-based system, used for various operations including growth monitoring, fertilizer management, disease identification, and crop yield prediction, etc [2]. Important decisions can be made using this information during the crop growing period to support management decisions. In this context, UAV-based high-resolution remote sensing is considered one of the most important technologies [3]. It potentially supports crop monitoring, providing an effective source for precision agriculture over the past few decades [4]. Remote sensing systems can monitor crop vegetative traits over different spectral wavelength ranges. In the past, remote sensing data was obtained using satellites and manned aircraft for crop monitoring. However, satellite remote sensing is often not a suitable option due to its spatio-temporal limitations and environmental conditions (clouds) mainly hinder its reliable use [5]. When it comes to the use of manned aircraft, costs are usually high, and data collection often requires more than one flight, which is not possible at this high cost.

UAV-based high-resolution remote sensing technology has given a new dimension to the agriculture sector. The use of UAV's for the surveillance of crops is highly effective as compared to the previous methods and offers great potential for capturing field data in each of the modes [6]. The modernization of UAV-based IoT technology is considered the future of remote sensing in agricultural management. The UAV's data gathering ability at low altitudes, a few centimeters, has an impact on high spatial resolution images of an object [7]. This improves the performance of surveillance systems and temporal resolution. Moreover, it increases the data acquisition flexibility, efficiently covering a larger area in less time and easy-to-use compared to manned aircraft [8]. UAV's equipped with a variety of sensors ranging from multispectral to thermal range, boosted the ability to respond on time. This article focuses on the most commonly used UAV imagery exploitation and processing techniques in agriculture. This is important because it can largely fill the absence of a standardized workflow, which is a major shortcoming and affects the widespread use of UAV systems. This fact has resulted in a variety of heterogeneous methods and procedures being written from many research articles for the same goal. It is most important to review the study of recent research work as it is a growing research area. This article expands on a review of the most recent studies regarding UAV-based applications, based on the most common techniques applied to UAV imagery in recent work for crop monitoring. The main goal is to identify the most commonly used UAV sensors in practice for each type of application.

II. ANALYTICAL FRAMEWORK

A. Application of UAV in agriculture

First, In the modern era, UAV technologies are being successfully used in the agricultural system (Table.1) such as site-specific nutrient management (SSNM), phenotyping, weed mapping, water stress, crop residues cover mapping, and disease identification, etc.

B. Weed Mapping

Weeds are undesirable vegetation which, grows within crops. These inequalities create competition for crop growth and development [29].

Table 1. UAV TECHNOLOGIES USED IN VARIOUS STUDIES.

S.No	Sensor	Application	Crop	Study area	Reference
1	Multispectral	Growth monitoring and yield estimation	Wheat	China	[9]
2	Multispectral	Plant Nitrogen	Wheat	China	[10]
3	Multispectral	Height Estimation	Corn	Japan	[11]
4	Hyperspectral	Disease (powdery mildew) detection	Squash	USA	[12]
5	Multispectral	Water Stress	Maize	China	[13]
6	Multispectral	Vigor and Yield estimation	Maize	Ghana	[14]
7	Multispectral	Weed mapping	Rice	Italy	[15]
8	Multispectral	Grain yield prediction	Rice	China	[16]
9	Multispectral	Plant Phenotyping	Wheat	UK	[17]
10	Hyperspectral	Plant Nitrogen, Leaf area index (LAI), and Chlorophyll	Wheat	Germany	[18]
11	Hyperspectral	Biomass estimation	Wheat	China	[19]
12	Hyperspectral	Fungal disease identification	wheat	Sweden	[20]
13	Hyperspectral	Plant stress (late blight disease)	Tomato	USA	[21]
14	Hyperspectral	Disease identification	Sugar beet	USA	[22]
15	Multispectral	Disease monitoring	Wheat	China	[23]
16	Multispectral	Disease identification	Rice	USA	[24]
17	Hyperspectral	Rice characterization	Rice	Japan	[25]
18	Hyperspectral	Water Stress	Potato	Colombia	[26]
19	Multispectral	Water stress	Maize	China	[27]
20	Multispectral	Disease	Wheat	China	[28]

Thus herbicide spraying throughout the field is the last option for the farmers. Traditionally farmers spray herbicides all over the area. This overuse of herbicides is harmful to standing crops as well as the environment. Site-specific weed management (SSWM) can be used to overcome the above problems. Under this, instead of spraying in the entire field, the required place can be identified with the help of a weed cover map. An experiment on the same topic was conducted in 2018 by Stropiana et al. [30] in which they used multispectral UAV data for early-season weed mapping in rice crops. This research approach is based on unsupervised classification and cluster labeling based on geocoded data obtained from'in situ observations.

C. Crop Growth and Development

UAV's are also often used for Crop growth and development. The lack of systematic tools for crop monitoring mainly hinders the efficiency and quality of agricultural production. This problem is also affected by environmental variability, resulting from changes in the microclimate of crops that threaten agricultural production. Regular data collection and visualization provide insights into crop growth status based on observed several field parameters variability [31].

D. Nutrient Estimation

It can be used to identify the crop nutrient requirement. Nitrogen content can be used to determine the need for additional fertilizer or other management actions. Currently, the most common method of determining nutritional status is through plant color guides, which do not allow for quantitatively rigorous evaluation [32]. More accurate evaluations require laboratory-based chemical analyses, which are time-consuming and the correct interpretation of the data requires the application of specific methods. A large proportion of studies of nutritional deficiencies found in the literature employ images captured by satellites [33]. Although some recently launched satellites can provide submeter ground resolution, they are still too coarse for to be analyzed plant individually, meaning that in several cases a deficiency can only be identified, when it's already extensive. On the other hand, UAVs can provide ground sampling distances of less than one centimeter without the high price and operative complications allied with manned aircraft [34].

E. Leaf Area Index (LAI)

In addition, the information acquired by the UAV's can be used for the creation of three-dimensional digital maps of the crop, and the measurement of various parameters, such as crop height, the distance between rows or between plants, and LAI [35]. UAV's offers the potential to systematically collect various crop information, therefore farmers could plan the timing of harvesting and soil and yield pathogens, or even identify possible management errors in a controlled manner.

F. Irrigation Management

Irrigation is very important to manage while the crop growing period. Globally approx 70% of the water is consumed for the crop irrigation area, highlighting the major facts of precision irrigation technique demands. Precision techniques can efficiently improve water use so that the resources are applied efficiently i.e. in the right quantity at the right places and time [36]. The major irrigation required area is detected which can help the farmers to save resources and time. At the same time, such methods can mainly improve crop quality and productivity. In the context of precision, the agriculture field is divided into different irrigation regions, to accurately manage the available resources. The use of Unmanned Aerial Vehicles including appropriate sensor varieties makes it conceivable to recognize parts that require water. At the same time, the exceeding technologies permit the production of specific maps that demonstrate the morphology of the soil ecosystem, thus associated with the more effective irrigation development of each crop individually [37].

G. Disease Identification

Plant disease identification using unmanned aerial vehicle (UAV) images is helpful to the dynamic control and monitoring in large capacities. It provides novel tools for enhanced vegetation health monitoring by providing data with very high spatio-temporal resolutions [38]. These platforms also pose distinctive defies and approaches for health appraisals must be legalized before use. A time-series dataset from a UAV platform can be extensively used for monitoring disease stress [39].

III. METHOD

A. UAV Data Acquisition and Processing

UAVs equipped with different specialized sensors are becoming potent sensing systems that complement IoT-based practices [40]. The potential role of the sensors is the detention of high-spatial and temporal resolution images, which can support vegetation characteristics monitoring. A variety of different sensors can be used in crop monitoring depending on the different parameters. Nevertheless, the necessities for low payload capability and the application of small platforms pretense some restrictions on the assortment of the used sensor. The key principle that the sensors need is lesser weight, size, and low energy consumption. All of the above parameters must be pooled with the capability to detention high-resolution imageries. Contemporary commercial sensors conforming with the exceeding boundaries that are widely used for Precision Agriculture, primarily belong to the four types of sensors (figure.1).

In addition to these four types of sensors, other sensors can also be used, such as light detection and ranging (LiDAR) or laser scanners. It is well-established equipment extensively used for the various research field, though they are typically used for terrestrial-ecosystem scanning [41]. The data attained through these sensors can be treated for plant biomass monitoring, vegetation vigor, soil moisture content, and other significant crop features at the altered growth stages [42].

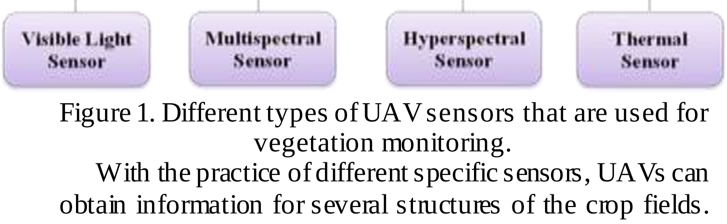

Figure 1. Different types of UAV sensors that are used for vegetation monitoring.

With the practice of different specific sensors, UAVs can obtain information for several structures of the crop fields. Though, still, there is no consistent workflow or well-known methods to follow for evaluating and visualizing the information assimilated. Generally used image processing approaches to examine UAV imagery for Precision Agriculture tenacities are as follows:

A. Photogrammetry Techniques

Photogrammetry concerns the precise restoration of an object from many overlapped images. These techniques can process the 2D datasets and create symmetrical associations between the object and different images, attaining 3D models. To create the 3D models, photogrammetry needs at least double overlapping imageries of the targeted object, that is captured from different points of view. This kind of procedure can be used for extracting terrain models or three-dimensional digital surface models [43].

UAV's low-altitude data acquisition permits the creation of 3D models with a high spatial resolution compared to satellite remote sensing [44]. Though, the assortment of temporal imageries is required to have information for the complete field under study. Therefore, in many cases, it is essential to assemble several overlapping imageries to make Digital Elevation Models (DEMs) of the crop fields or create orthomosaic. The 3D models contain information about the 3D features of the particular crops based on their characteristics e.g., height, color, leaf structure, canopy, and density, etc [45].

It can be very useful for applications that can exploit only RGB imagery. The mechanisms studied indicated that photogrammetric systems are normally used in all types of applications as they are also necessary to generate different vegetation indices-based maps [46]. In addition, the 3D information they contain is very significant and is frequently used with other methods.

B. Machine Learning Methods

Machine Learning (ML) has been used to practice the data assimilated, for forecast or identification purposes, with abundant consequences in countless fields, such as agriculture, medical systems, marketing, soil biology, etc [47]. Machine learning practices are widely used in precision agriculture to attain the information from the huge quantity of data assimilated through the UAVs. It is also capable to assess some factors concerning the vegetation growth rate, diseases identification, or distinguishing entities in the imageries. Its usage has improved a lot in recent times due to the dissolute improvements taking place, especially in the deep learning research field.

C. Spectral Vegetation Indices

Spectral vegetation indices (VIs) are one of the most standard products of remote sensing for precision agriculture research study. They use diverse precise combinations or alterations of at least two spectral wavebands of the electromagnetic spectrum, considered to exploit the involvement of the vegetation features while reducing the exterior impenetrable influences [48]. It can provide consistent spatio-temporal information about the different crop parameters. In many cases, numerous VIs are calculated and used to define inferences. They can be designed based on evidence of either respective imageries or after the creation of an orthomosaic image representing the entire crop field area [49]. Computing different vegetation indices may help in the identification of different crop characteristics, for example, plant physical and biological parameters. Meanwhile, the handling of data may be time-intense, numerous software and methods have been established to permit rapid data processing. The most commonly implemented software resolutions in the mechanism used to support and speed up the data analysis practice are Erdas Imagine, eCognition, and PixelWrench, etc [50].

IV. Limitation

Although for PA the UAVs usage are increasing recently some restrictions are also there that inhibit their extensive practice. The lack of a consistent workflow leads to the approval of ad-hoc measures for arranging its applications, a fact that weakens the significant participants. In addition, as crop monitoring and management need data-intensive actions for the utilization of the acquired images, expert workforces are generally required [51]. This means that an average agriculturalist might need exercise or even been enforced to charge specialists to support the processing of the image, which may be expensive. This fact may forbid the acceptance of UAV machinery from distinct farmers with only insufficient and lesser agricultural areas. The huge investment rate to procurement the Unmanned Aerial System is another exorbitant aspect [52]. Compelling into depiction the fast advances in UAV machinery and the sensors practice in crop monitoring, the price of the Unmanned Aerial Systems will be compact shortly time. Applied restrictions, such as the flight period, are also probably to be resolved by the developments in equipment [53]. These advances will confirm that agriculturalists can gain more with the help of UAVs.

V. CONCLUSION

The application of UAV remote sensing has received a lot of consideration in the last few years, hence it is being considered as a better option in the coming future, which remains the focus of attention. In this article, the most commonly used applications, types, and uses of unmanned aerial systems for the agricultural sector are presented. Using UAV systems, a GIS land management system to achieve precision agriculture could be executed for agricultural management. As the increasing population and natural resources such as agricultural, water, and land is being limited, UAV-based precision agriculture becomes and significant research area. This short review will serve as a starting point for professionals to understand the usage of UAVs in agriculture.

Conflicts Of Interest

The author declare no conflict of interest.

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