Role of Hyperspectral imaging for Precision Agriculture Monitoring

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Abstract*: *In the modern era precision agriculture has started emerging as a new revolution. Remote sensing is generally regarded as one of the most important techniques for agricultural monitoring at multiple spatiotemporal scales. This has expanded from traditional systems such as imaging systems, agricultural monitoring, atmospheric science, geology and defense to a variety of newly developing laboratory-based measurements. The development of hyperspectral imaging systems has taken precision agriculture a step further. Because of the spectral range limit of multispectral imagery, the detection of minute changes in materials is significantly lacking, this shortcoming can be overcome by hyperspectral sensors and prove useful in many agricultural applications. Recently, various emerging platforms also popularized hyperspectral remote sensing technology, however, it comes with the complexity of data storage and processing. This article provides a detailed overview of hyperspectral remote sensing that can be used for better estimation in agricultural applications.

***Keywords*: Remote Sensing, Hyperspectral Imaging System, Precision Agriculture, Monitoring.**

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I. INTRODUCTION

Over the past decade, vegetation characterization has been recognized as an important indicator for understanding ecosystem adaptation to environmental change [1]. The absence of a spatiotemporal variability description of plant traits is a major source of uncertainty in simulating the global flow of carbon and water cycles by terrestrial-biosphere models [2]. The study of crop monitoring during its growth period is essential for achieving higher yield productivity. Conventional methods are highly time consuming, hence requiring the use of advanced equipment/instruments in modern non-invasive monitoring systems. In this context, recent studies have successfully confirmed the potential of hyperspectral remote sensing. It has been widely used to characterize various parameters of the crop, such as water stress [3], nutrient assessment [4], disease detection [5], and crop yield modeling [6]. The physico-chemical properties of plants are captured precisely as spectral signatures. These unique signatures are based on plant biophysical traits and environmental conditions [7]. It is extremely important to recognize the requirement of the crop during the growth period for better crop management. Therefore, it is important to review this area to build a more efficient decision-making system. The present study proposes a framework for the role of hyperspectral imaging systems for precise agricultural monitoring. This brief survey will help professionals to get an initial overview of hyperspectral remote sensing.

Hyperspectral and multispectral are two different remote sensing technologies that have been used in many applications over the past decades. The use of multispectral remote sensing is spatially and spectrally limited compared to a hyperspectral imaging (HSI) system [8]. The large number of narrow spectral bands acquired by hyperspectral sensors allows the extraction of minute features that cannot be captured by the broad spectral range of multispectral sensors [9]. The HSI data are connected in such a way that each pixel or spatial location covers the data for all measured wavelengths [10]. Therefore, hyperspectral imagery is actually a three-dimensional cube of the dataset (Figure 1). However, these advantages come with system complexity due to the lighting, filtering medium, optical design, and primary disadvantages including high cost and computational complexity [11].

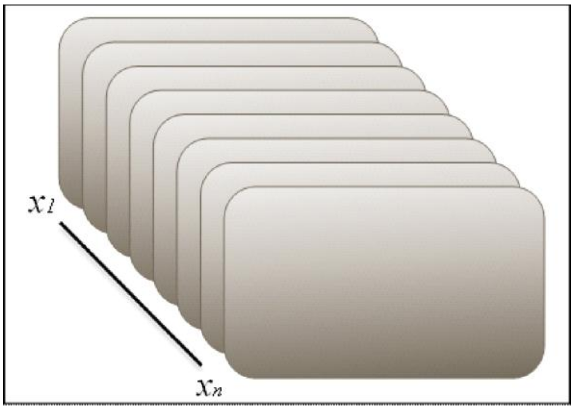

Fig. 1. Hyperspectral Image Cube

A. Data Acquisition Platforms

Hyperspectral sensor platforms are commonly available as space-based (satellite), aerial (airplane, Unmanned Aerial Vehicle) and ground-based (handheld or stationary) systems. Airborne hyperspectral remote sensing was first introduced in 1982 as NASA's Airborne Imaging Spectrometer. Subsequently, aerial hyperspectral imagers such as AVIRIS, CASI, Hypercam, and HEMP have been developed [12]. Aerial images have more spatial and spectral resolution than their space borne counterparts, are greater in swath width and spatial coverage [13]. Satellite imagery is capable of acquiring the image of the whole world without any hindrance. However, the shortcoming of satellites is their orbital passing period and cloud cover, whereas aerial platforms are more expensive, but can be planned as per requirement [14].

B. Hyperspectral Images Processing

The hyperspectral data received by various sensors and platforms are provided in raw format which mainly requires pre-processing to obtain spectral information. The pre-processing of the hyperspectral image includes atmospheric, radiometric, orthorectification and geometric correction [15]. For satellite imagery, geometric and orthorectification corrections are usually obtained by the agency providing the data and atmospheric and radiometric corrections can be completed by users. In UAV-based imagery, users are required to conduct the above processing steps and finalize a suitable processing method. For example, DEM (Digital Elevation Model) and GCP (Ground Control Points) are required to perform geometric and orthorectification corrections [16]. Hyperspectral sensors acquire a large number of spectral bands in a very short period, of which only a few bands are relevant to the study. Therefore, the removal of bands with spectral inconsistency is also a necessary procedure in the pre-processing of hyperspectral datasets [17].

C. Data Dimensionality Reduction

Dimensional reduction techniques are applied to increase the processing efficiency and accuracy of the classifiers at low computational cost [18]. Several studies have stated that optimized bands significantly improve the explanatory power [19]. Band-band correlation (BBR2), minimum noise fraction (MNF), principle component analysis (PCA), clustering/classification, artificial neural networks (ANN) and spectral libraries are some examples of techniques used in hyperspectral data.

Singh et al. (2020) performed band–band correlation (BBR2) and principal component analysis (PCA) on hyperspectral imagery to obtain the most optimal spectral bands for crop monitoring studies [20]. In the BBR2 method, the correlation matrix of all possible band combinations is used to obtain the optimal band. Whereas, PCA is a linear unsupervised technique, which minimizes the disjoint assemblies with a maximum variance [21]. It can be defined as an Eigen decomposition of the covariance matrix of the data. In another study [22], the MNF (minimum noise fraction), and SVD (singular value decomposition) method were used, and suggested an algorithm based on discriminant analysis for supervised classification. Huang et al. (2019) reviewed the various data dimension reduction techniques and summarized them on the basis of 'image transformation' [23]. Thenkabail et al. (2013) cited the data dimensionality problem and recognized several spectral bands that are more important for crop characterization [24]. Spectral libraries are generated based on wavelength variation versus pixel reflectance, which is used to identify object-specific properties [25]. Lu et al. (2020) studied various dimension reduction methods, such as wavelet transform, artificial neural network (ANN), uniform feature design (UMD) [26]. Generally, pre-processing is an important step to enhance hyperspectral image quality and further data analysis [27]. These methods eliminate redundant spectral bands and propose the most suitable spectral bands for study [28].

II. USE OF HYPERSPECTRAL IN PRECISION AGRICULTURE

Mapping early plant disease and pest outbreak are essential for agricultural management to reduce economic losses, which can provide the greatest benefits [29] Hyperspectral remote sensing plays a vital role in boosting farming system, thus helping agro economies to grow. Agriculture can take benefit from these emerging technologies to optimize fertilizers exercise, yield prediction, irrigation, and weed identification (Table.1). Traditionally, crop mapping has required time-intensive surveys; however, with the specialized hyperspectral sensor in this field, the mapping of crops can be classified in an effective manner in the shortest possible time [30].

HSI provides information in several contiguous spectral wavebands; However, many applications usually require data only from a selected frequency which is determined according to the absorption and reflection characteristic of the object being observed. The absorption characteristics of an object are affected by the variability of features, including its content, composition, concentration, and constituents. In agricultural applications, absorption properties in the visible region are controlled by the concentration and amount of photosynthetic pigments [8]. The inner leaf structure i.e., the layers of the structure, shape and size of the leaf has a great influence in the near visual region. Other factors include concentration of biochemical and moisture content. In general, the spectral signature of vegetation exhibits many distinctive features, such as green peak, chlorophyll content, red-edge, NIR plateau and water absorption characteristics [11]. Understanding the causes of variation in plant spectral reflectance is critical for effective hyperspectral data processing.

Multiple vegetation indices (VIs) are an advantage for various applications. VIs are simple arithmetic combinations of the spectral reflectance at a particular frequency of an object, which change depending on the characteristics of the object [46]. These types of indices are of great benefit in agricultural management, by using them various types of information can be assessed in time about crop health and yield estimation, which can be beneficial in the form of higher yield [47]. For example, Normalized Difference Vegetation Index (NDVI), Enhanced vegetation index (EVI) and Soil-Adjusted Vegetation Index (SAVI).

TABLE I. HYPERSPECTRAL INSTRUMENT USED IN VARIOUS AGRICULTURAL MONITORING STUDIES.

Sl. No.	Platform	Sensor	Spectral Range	Application	Crop	Study area	Reference
1	Hand-held Spectrometer	ASD FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO, USA).	350–2500 nm	Plant growth monitoring	Rice	China	Xie et al. 2013
2	Hand-held Spectrometer	ASD FieldSpec Spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA).	350–2500 nm	Plant Nitrogen stress	Wheat	India	Ranjan et al. 2012
3	Unmanned aerial vehicle (UAV)	DJI S1000 UAV, SZ DJI Technology Co., Ltd., Sham Chun, China.	450–950 nm	Plant height estimation	Wheat	China	Tao et al. 2020
4	Hand-held Camera	SPECIM IQ Hyperspectral camera.	400-1000 nm	Plant Viral disease detection	Vine	Columbia	Nguyen et al. 2021
5	Hand-held camera	ImSpector V10E, Spectral Imaging Ltd., Finland.	385–1000 nm	Water Stress	Apple	USA	Kim et al. 2011
6	Aircraft	Micro-Hyperspec VNIR model, Headwall Photonics, Fitchburg, MA, USA.	400-1000 nm	Plant Phenotyping	Wheat	Spain	Gonzalez-Dugo et al. 2015
7	Airborne	Hyperspectral imaging camera with electron multiplying CCD detector.	457.2-921.7 nm	Weed mapping	-	USA	Yang et al. 2010
8	Airborne	Model: A-series, Micro-Hyperspec Airborne sensor, VNIR Headwall Photonics, Fitchburg, Massachusetts, US.	380-1000 nm	Grain yield prediction	Wheat	USA	Montesinos-López et al. 2017
9	Hand-held Spectroradiometer	ASD FieldSpec Spectroradiometer	350–2500 nm	Plant Nitrogen, Leaf area index (LAI), and Chlorophyll	Potato	Netherlands	Clevers et al. 2011
10	Unmanned aerial vehicle (UAV)	DJI Matrice 600 Pro Hexacopter equipped with a Headwall Nano-Hyperspec (Headwall Photonics Inc., Bolton, MA, USA.	400-1000 nm	Biomass and yield estimation	Potato	China	Li et al. 2020
11	Hand-held spectrometer	Pika XC2 hyperspectral imaging camera.	400–1000 nm	Plant disease identification	Soybean	USA	Nagasubramanian et al. 2019
12	Satellite	Airborne visible infrared Imaging spectrometer (AVIRIS).	400-2500 nm	Plant stress (late blight disease)	Tomato	USA	Zhang et al. 2003
13	Hand-held spectrometer	Hyperspectral imaging line scanning spectrometer (ImSpector V10E).	400-1000 nm	Disease identification	Sugar beet	Germany	Mahlein et al. 2012
14	Unmanned aerial vehicle (UAV)	Hyperspectral sensor (UHD 185 firefly, Cubert GmbH, Ulm, Baden-Württemberg, Germany).	450-950 nm	Disease (Yellow Rust) monitoring	Wheat	China	Zhang et al. 2019
15	Unmanned aerial vehicle (UAV)	UHD 185 Firefly (UHD 185).	450-950 nm	Growth monitoring	Rice	Germany	Yue et al. 2017

Hyperspectral Remote Sensing is one such modern technology which can be used to greatly benefit precision agriculture. Mainly in agriculture requirements, hyperspectral imaging can be used for various parameters such as pest monitoring, yield estimation, water requirement and crop classification etc.

III. LIMITATIONS

The use of hyperspectral sensors has been increasing in recent times for precise agricultural monitoring, but it also has some limitations that impede its practice. The inadequacy of a consistent workflow undermines adequate usages. In addition, the application requires a data-intensive program and skilled experts. The result is that a farmer may need to practice or hire an expert to assist with data processing and use. To reflect rapid developments in hyperspectral sensors used in crop monitoring, costs will need to be compacted quickly.

IV. CONCLUSIONS

In recent times hyperspectral sensors are being used in precision agricultural monitoring. Generally, it can be defined as the observational use to improve agricultural resource practice and management. Hyperspectral remote sensing provides information through several contiguous spectral bands; which helps in many agricultural applications. This review will help to gain preliminary knowledge and initial opinion for agricultural researchers or professionals looking to understand hyperspectral imagery use in agricultural monitoring.

CONFLICT OF INTEREST

The authors have no conflict of interest.

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