Hyperspectral Remote Sensing for Agriculture: A Review

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ABSTRACT
Hyperspectral remote sensing is used for wide range of application. Hyperspectral data provides more than 200 narrow wavelength bands which provide significant information about all biological and chemical properties of material. Hyperspectral remote sensing is widely used in various applications like agricultural and soil research, mining application, crop management application, drought condition assessment, plant species classification, water body analysis, mineral analysis etc. This paper mainly reviews the concept of hyperspectral remote sensing; processing of hyperspectral data; different vegetation indices defined by researcher; the applications of hyperspectral data for agricultural.

General Terms
Hyperspectral Remote Sensing

Keywords
Hyperspectral data, Remote sensing, Spectral reflectance, Agriculture, Crop classification, Vegetation Index.

1. INTRODUCTION
1.1 Hyperspectral Remote Sensing
Hyperspectral remote sensing is known as imaging as well as non-imaging spectroscopy. Recent developments in remote sensing and geographic information system has directed the method for the advancing of hyperspectral sensors, which is a relatively new technology that is currently being used by researchers and scientists with regard to the recognition and identification of material, crop species, soil analysis, terrestrial vegetation, and man-made materials and background applications.

Hyperspectral remote sensing is used for over 100 years for analysis of various objects and their chemical as well as biological composition. But hyperspectral sensor offers an alternate and nondestructive technique for analysis of physical and chemical properties material. Spectroscopy can be used to detect specific absorption characteristics due to specific bonding in a solid, liquid, or gaseous material. Recently, with evolving technology progress, imaging spectroscopy has begun to focus almost all applications on the Earth. The idea of hyperspectral remote sensing began in the mid-80 and to this point has been used widely by geologists for the mapping of minerals.

Typically, hyperspectral sensors capture light in the range of 350 nm – 2500 nm. It covers the visible, NIR and SWIR frequency bands. Hyperspectral data is acquired over the range of tens to hundreds narrow spectral bands. However multispectral data is acquired over a relatively small number of broad spectral bands.

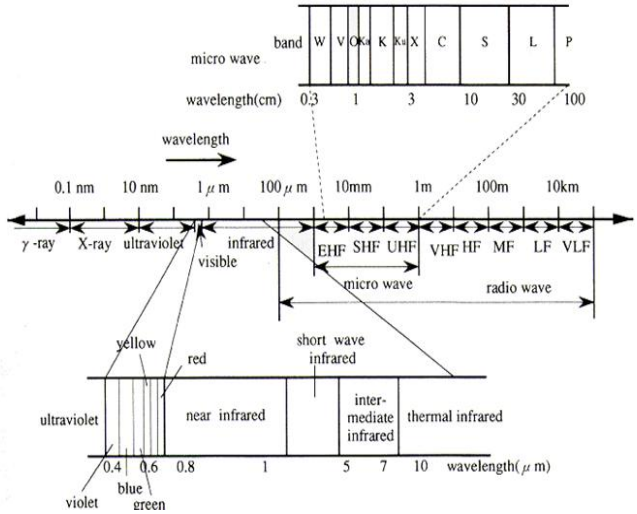

Fig.1: Bands used in remote sensing [1]

1.2 Spectral Reflectance
Remote sensing is based on the phenomena of reflected or radiated energy from different bodies. Entities having different surface characteristics redirect or absorb the sun's light energy in different ways. These properties of reflectance of material depend on the specific material and its biophysical and biochemical state, the surface irregularity as well as the geometric circumstances (e.g. angle of incidence). Color, structure and surface texture of material are the most important surface features.

These alterations make it probable to identify different surface features or materials by analyzing their patterns of spectral reflectance or signatures. These signatures can be pictured in so called spectral reflectance curves as a function of wavelengths. Following figure shows spectral signature of soil, water, and vegetation [2].

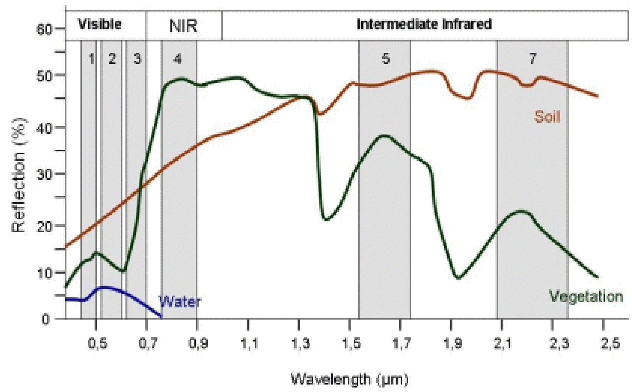

Fig.2: Spectral signatures of soil, vegetation and water, and spectral bands of LANDSAT 7

2. HYPERSPECTRAL REMOTE SENSING FOR AGRICULTURE

2.1 Spectral Properties of Vegetation

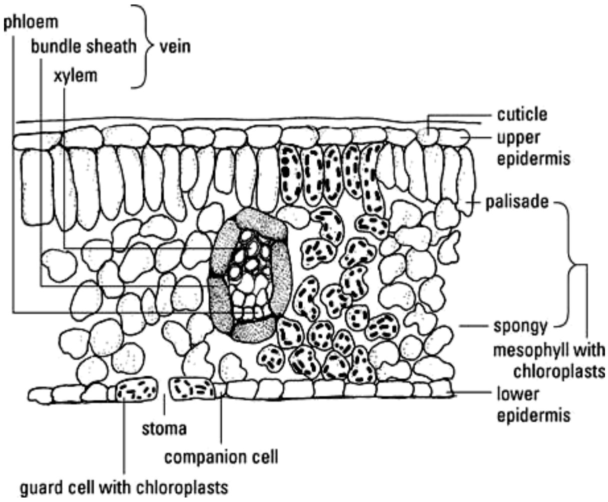

Fig.3: Internal structure of leaf

Leaves play very important role in photosynthesis process as well as protecting plants. There are three major classes of pigments that can be found in plants:

- Chlorophyll
- Carotenoid
- Anthocyanin

Chlorophyll-a and chlorophyll-b functioning for converting light energy into chemical energy which is used by plant. Carotenoid exhibits strong light absorption in the blue region of spectrum and it non-uniformly distributed in photosystem [3]. For diagnosing physiological state of plant in development and adaptation to different environmental condition and plat stresses, the changes in leaf carotenoid content and its proportion with chlorophyll are widely used. The anthocyanin pigments are responsible for red coloration in higher plants.

Traditionally, for pigment analysis of plants, wet chemistry methods were used. But recently researcher has found hyperspectral remote sensing as alternative method for analysis of biological and biochemical properties of plants. Analysis of reflectance variation is general approach used for study by many researchers [4].

As we can see in Fig. 2, in the range of 400–700 nm, absorption by leaf pigments is the best substantial process primarily focused to low reflectance value as well as transmittance values. This is because of

- chlorophyll a and chlorophyll b,
- carotenoids,
- xanthophyll
- polyphenols,

And all pigments have overlying absorption characteristics. 65% of the total pigments are Chlorophyll a (Chl a) and chlorophyll b (Chl b). Chlorophyll a (Chl a) is the main element of developed plants species. Chl a shows extreme absorption of light in the 410–430nm and 600–690 nm region, whereas in 450–470 nm range chlorophyll b expresses extreme absorption. These absorption band brings a reflectance peak at about 550 nm in the green domain. Carotenoid shows absorption of light most efficiently in the range of 440 and 480 nm. Polyphenols shows absorption of light with declining amount of intensity from the blue region to the red region and active when the leaf is dead [5]. In the vegetation's canopy species, Chl b expresses the feature of absorption at short as well as long wavelengths in the visible bands.

In the domain range of 700–1300 nm, leaf pigments and cellulose are radiant, so that maximum values of reflectance and transmittance will be observed and absorption is very low. Interior scattering within the leaves at the air, cell, and water interfaces is reason behind it [6]. The reflectance level in the near-IR region rises with increasing inter-cell spaces, cell layers and cell size. Phenomenon of scattering happens mainly due to multiple refractions and reflections among the air spaces and hydrated cellular walls. In the shortwave-infrared (SWIR) region, leaf photosensitive properties are mainly affected by water and additional foliar constituents. The 1450, 1940 and 2700 nm are the major water absorption bands and secondary features occurs at 960, 1120, 1540, 1670 and 2200 nm [7].

Best hyperspectral narrow bands can be determined on a comprehensive review and study of the literature for crops comprises:

(a) Detecting redundant bands,

(b)Demonstrating by relating crop variables with hyperspectral bands and indices,

(c) Finding bands that are useful to distinguish crops and their genotypes,

3. DATA PROCESSING AND ANALYSING METHOD

Data processing and analyzing methods followed for designing hyperspectral remote sensing model for agricultural applications shown in following Fig. 4.

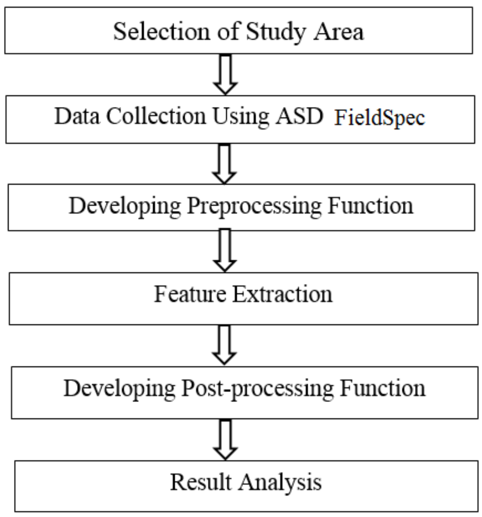

Fig.4: Designing hyperspectral remote sensing model

In very first step, selection of study area consists of forest or vegetation. Data can be collected either directly from field or in laboratory in controlled condition. While collecting data, care must be taken of instrument height, FOV etc. ASD FieldSpec spectroradiometer is used for collecting data. Spectral signature contains data in 350-2500nm range.

After collecting data, preprocessing can be done. For extracting features and selecting optimal bands from collected data various methods have been used by researcher. Some of them are as follows.

- Principal Component Analysis (PCA) depending on high factor loadings or Eigen vectors [8],
- Uniform Feature Design (UMD) by decreasing dimensionality of dataset retaining spectral shape information [9],
- Wavelet Transforms which analyzes data at different scales [10] and
- Artificial Neural Network (ANN) [11].

All methods mentioned above have some merits as well as demerits.

Post-processing functions can be designed according to application like

- Crop discrimination
- Identification of canopy species in tropical forest
- Land cover application
- Detecting leaf and plant biophysical and biochemical property
- Detecting vegetation processes and functions
- Detecting crop management, plant stress, and diseases etc.

4. HYPERSPECTRAL REMOTE SENSING APPLICATIONS FOR VEGETATION

4.1 Crop Discrimination and Spectral Characterization

Advantage of capturing and discriminating subtle differences among crop types is because of high spectral resolution of hyperspectral data, but disadvantage of hyperspectral data is it contains redundant information due to which problem occurs for calculation. The best and frequently used method to decrease the number of wavebands is feature selection and using discriminant statistics such as PCA and SDA, highest discriminant bands are selected. Several researchers [12], [13], [14], [15] have used these methods to select instructive bands in hyperspectral data and discriminated vegetation types or species.

Manjunath et al. [16] differentiated among ornamental plants, pulses and Cole crops using hyperspectral data. He used SDA technique to select optimum bands. His research presented that in NIR and early MIR regions has the best four bands for pulse crop discrimination, i.e. 750, 800, 940 and 960 nm. Cole crops discrimination is primarily determined by the green, red and NIR bands of 550, 690, 740, 770 and 980 nm. The research study presented that for discriminating flowers 420, 470, 480, 570, 730, 740, 940, 950, 970, 1030 nm bands are useful.

Sahoo et al. [17] discovered that with the help of SDA technique for the feature selection and Jeffries–Matusita (J–M) distance as a distinguishing index, there is possibility of discrimination of 70 wheat genotypes from proximal hyperspectral reflectance data.

Kumar et al. [18] for understanding spectral performance of tea plants in regard with plant type, plantation age, various growing stages, pruning status, light conditions and disease incidence, carried out field hyperspectral data analysis. He used Stepwise Discriminant Analysis (SDA) and Principal Component Analysis (PCA) to recognize the proper or suitable bands for retrieving the above mentioned information from crops hyperspectral database.

Miglani et al. [19] evaluated from satellite data of Hyperion classifying various winter crops such as mustard, sorghum wheat, sugarcane and potato. He used band-to-band correlation analysis and Principal Component Analysis (PCA) as the feature selection step.

4.2 Estimation of Biochemical and Biophysical Properties of Crops, Plant Stress and Light Use Efficiency

By using different types of vegetation indices estimation of biochemical and biophysical properties of crops is possible. Vegetation indices that are used by many researchers have shown in following table.

Table 1. Vegetation Indices used by researchers

Index	Equation	Reference
Structure(LAI, Green Biomass, Fraction)		
EVI	$2.5 * (R_{NIR} - R_{red}) / (R_{NIR} + 6 R_{red} - 7.5 R_{blue} + 1)$	[20]
Green NDVI	$(R_{NIR} - R_{green}) / (R_{NIR} + R_{green})$	[21]
NDVI	$(R_{NIR} - R_{red}) / (R_{NIR} + R_{red})$	[21]
SR	R_{NIR}/R_{red}	[22]
NDWI[a]	$(R_{857} - R_{1241}) / (R_{857} + R_{1241})$	[23]
WBI[b]	R_{900} / R_{970}	[24]
ARVI[a]	$(R_{NIR} - [R_{red} - \gamma * \{R_{blue} - R_{red}\}]) / (R_{NIR} + [R_{red} - \gamma * (R_{blue} - R_{red})])$	[25]
SAVI[a]	$[(R_{NIR} - R_{red}) / (R_{NIR} + R_{red} + L)] * (1 + L)$	[26]
VARI[a]	$(R_{green} - R_{red}) / (R_{green} + R_{red} - R_{blue})$	[27]
VI_{green}[a]	$(R_{green} - R_{red}) / (R_{green} + R_{red})$	[27]
Biochemical		
Pigments		
SIPI[b]	$(R_{800} - R_{445}) / (R_{800} - R_{680})$	[28]
PSSR[b]	$(R_{800} / R_{675}); (R_{800} / R_{650})$	[29]
PSND[b]	$[(R_{800} - R_{675}) / (R_{800} + R_{675})]; [(R_{800} - R_{650}) / (R_{800} + R_{650})]$	[30]
PSRI[b]	$(R_{680} - R_{500}) / R_{750}$	[31]
Chlorophyll		
CARI[b]	$[(R_{700} - R_{670}) - 0.2 * (R_{700} - R_{550})]$	[32]
MCARI[b]	$[(R_{700} - R_{670}) - 0.2 * (R_{700} - R_{550})] * (R_{700} / R_{670})$	[33]
CIred[b]	$R_{NIR} / R_{red\ edge} - 1$	[34]
Anthocyanins		
ARI[b]	$(1 / R_{green}) - (1 / R_{red\ edge})$	[35]
mARI[b]	$[(1 / R_{green}) - (1 / R_{red\ edge})] * R_{NIR}$	[35]
RGRI[b]	R_{red} / R_{green}	[36]
ACI[b]	R_{green} / R_{NIR}	[37]
Carotenoids		
CRI1[b]	$(1 / R_{510}) - (1 / R_{550})$	[38]

CRI2[b]	$(1 / R_{510}) - (1 / R_{700})$	[39]
Water		
NDII[a]	$(R_{NIR} - R_{SWIR}) / (R_{NIR} + R_{SWIR})$	[40]
NDWI[a], WBI[b]	See Above	
MSI[a]	R_{SWIR} / R_{NIR}	[41]
Light Use Efficiancy		
RGRI[b], SIPI[b]	See Above	
PRI[b]	$(R_{570} - R_{531}) / (R_{531} + R_{570})$	[42]
Stress		
MSI[a]	See Above	
REP[b]	L (max first derivative: 680-750nm)	
RVSI[b]	$[(R_{714} + R_{752}) / 2 - R_{733}]$	
Note: Repeated indices are used for multiple purpose [a]: Narrow band equivalent of a broad band index [b]: Strictly narrow band/ Hyperspectral band		

Most vegetation indices are developed for broadband systems, but many of them are hyperspectral. Those VI's have several applications like estimation of LAI, focus on seasonal changes in soil moisture and canopy biochemistry etc.

4.3 Monitoring Biotic Stress

Plant gives response to abiotic and biotic stresses in a various ways, for example, chlorosis or necrosis of photosynthetically active parts, stunted growth, leaf coiling, wilting, or in some cases decrease in leaf area due to severe defoliation. To compute visually these plant responses are problematic with satisfactory levels of accuracy and punctuality. However, electromagnetic energy reflected back from plant canopies affects amount and quality of these responses. Hyperspectral remote sensing was found to be capable to identify different stresses depending on the hypothesis that stresses obstructed with physical structure of the plants as well as photosynthesis and affect absorption of light energy and reflectance spectrum of plants.

5. CONCLUSION

Hyperspectral remote sensing has variety of application for agriculture. It makes us able to focus on discrimination of crops, determining plant stress and analyzing its reflectance response in stress condition, biochemical and biophysical parameter retrieval, diseases detection etc. Getting hold of and understanding of the elementary spectral signatures of plants is very significant task. Selection of optimum wavebands is significant, so many data mining and feature extraction techniques have been used for it. We can say hyperspectral remote sensing is best nondestructive analyzing method for assessing plants and crops characteristics.

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