

# Crop mapping using Hyperspectral remote sensed Image using Airborne Imaging Spectrometer.

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**Abstract:** Crop Analyst in India was taking about the healthy growth of economic vegetation of rare species; they decided to start controlling the invasion of these species. A major challenge encountered is to map the extent of its spatial spread. While satellite remote sensing and aerial photography have been available for many years, newer detection technologies such as hyperspectral sensors have made it possible to acquire large-scale laboratory-like spectra of rare species patches and surrounding natural grasses in the air.

In this study, crop (speices) was mapped using the Airborne Imaging Spectrometer for Application (AISA) sensor that records images at high spectral (9nm bandwidth, visible-infrared) and spatial (~1m) resolution. Ground spectra were measured using the FieldSpecPro Full Range (FR) spectroradiometer from Analytical Spectral Devices (ASD, 2006). The study area is a grass field within the National Forest. The AISA images were processed with three different classification methods.

**Key points:** Multispectral, Hyperspectral, Image Spectrometry, Scene-Based Empirical Approaches , Band ratio

## Multispectral remote sensing in agriculture

### Species crop mapping

Agricultural fields during the growing season have distinctly different color, pattern and texture from other land cover types such as forest and water. As a result, large-area crop mapping can be easily conducted from multispectral images at medium to coarse resolution. More detailed information can be extracted from multispectral images at high resolution to meet the requirements of site-specific farming (Barnes 1996).

Perhaps the most widely accepted method for image-based crop monitoring is to extract greenness and healthiness information by calculating band ratios or vegetation indices (Thorp and Tian 2004). Vegetation indices can be used to estimate soil properties such as organic matter (Dalal and Henry 1986; Shonk et al. 1991). Vegetation indices are also used for water stress detection (Barnes 1996). Many of these indices have been developed for use in remote sensing research over the past 30 years. Among them the most widely used one is the normalized difference vegetation index (NDVI; Ashley and Rea 1975). In addition to the NDVI, the other two most basic vegetation indices (VI) are ratio vegetation index (RVI; Jordan 1969) and difference vegetation index (DVI; Tucker 1979). These basic vegetation indices can easily separate vegetation spectra from other spectra such as soil and water. However, they are highly affected by soil background and other geometric/systematic factors. Several more advanced VIs are introduced such as Soil Adjusted Vegetation Index (SAVI; Huete 1988) and a similar Transformed Soil Adjusted Vegetation Index (TSAVI; Baret 1989) that reduces soil effect in the calculated VIs. Later a more advanced Modified Soil Adjusted Vegetation Index (MSAVI; Qi 1994) is introduced to interactively adjust for soil effect in each area instead of using a constant soil factor value as in SAVI. Vegetation indices have always been widely applied in agricultural studies.

### Rare species detection

Because of the small size of invading weeds and the spectral similarity with crops in the fields, the application of multispectral remote sensing in weed detection has been limited. It was examined the possibility of using multispectral remote sensing in detecting spider mite on cotton in

California. He also tested the feasibility of early detection using multitemporal data.

A lot of techniques were compared in his research, such as principal components analysis, classification and change detection. The implications of this research are bi-fold in that it tested the critical cut-off time of detecting invasive species and also looked at the trend of invasion by examining data in a series of time.

Low altitude and higher-resolution systems have potential to characterize weed texture (Smith 2003), but only after full growth when vegetation texture is formed. Although it is desirable to detect invasive species in early stage to allow corrective actions to be taken, multispectral remote sensing has limited capability of detecting infestation in very early stages (Smith 2003). I

It might be more useful in late-season weed infestation detection. Koger (2003) found that late-season weed infection in soybean fields could reach an accuracy of over 90% with NDVI derived from multispectral image.

The primary limit in detecting weed invasion with multispectral remote sensing comes from its broad band settings that conceal a lot of minor variation inside the real continuous spectra. In previous research, it was found that some of the background effects could be substantially reduced using narrow-band derivative-based vegetation indices (Elvidge 1995). Therefore hyperspectral remote sensing is more desirable when subtle spectral variation is needed in agricultural studies.

## Hyperspectral remote sensing in agriculture

### Image Spectrometry

Image spectrometry, a new technique for remote sensing of the earth, is technically feasible from aircraft and spacecraft platform. The airborne and spaceborne sensors are capable of acquiring images simultaneously in 100 to 200 contiguous spectral bands depending on application necessity and system configuration. The ability to acquire laboratory-like spectra remotely is a major advance in remote sensing capability. It is now possible to remotely identify a surface material on a pixel basis by examining its absorption features in the continuous reflectance spectrum (Goetz 1985). An example of material identification is shown in the following

Figure 1. The spectral resolution of the library spectra is 1 nm. All of the five materials are completely separable given good band selection and combination. If hyper spectral

remote sensors can obtain images with such high spectral resolution, the image could be directly referenced to the library spectra to perform material identification.

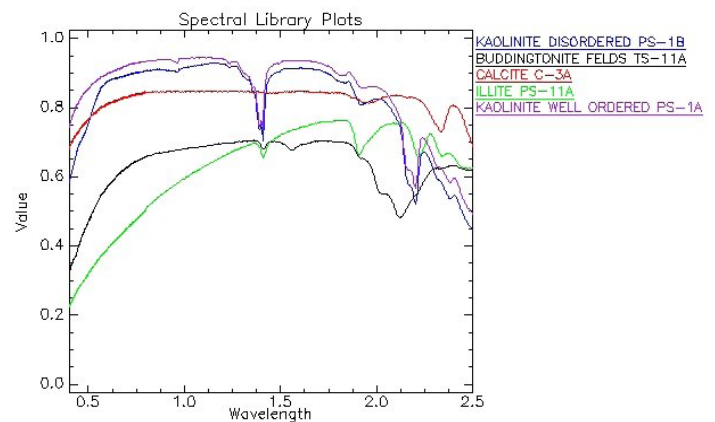


Figure 1: Sample spectral plot from JPL spectral library (ENVI 2002)

A considerable number of space borne or airborne spectroscopic devices with as many as 200 spectral bands are now flying in a number of countries. Despite the much narrower spectral bands being used, they can provide signal-to-noise ratios supporting 10-12 bit data systems with spatial resolutions of a few 10's of meters IFOV (Instantaneous Field Of View) from orbit and roughly 1 meter resolution for airborne sensors (Landgrebe 1993).

### Invasive species detection

The most extensive hyperspectral remote sensing agricultural application is perhaps precision farming. In precision farming, scientists care most about the healthy growth of economic vegetation. Therefore they will need hyperspectral remote sensing as tool to detect any phenomenon that is hampering the healthy growth of economic vegetation. Problems related to precision farming like malnutrition, pest invasion and weed infestation in a particular crop can be observed in a unique spectrum which is distinctly different from healthy vegetation (Gat, Erives, Maas and Fitzgerald 1999). Various approaches of hyperspectral data processing have been developed for invasive weed detection. For example, Garegani, et al. (2000) applied Minimum Noise Fraction (MNF) approach to detect stressed crops. Zhang (2003) used hyperspectral data to detect stress in tomatoes induced by late blight disease in California by using MNF rotated spectra as an input to Spectral Angle Mapper (SAM) classification.

More well-rounded invasive species detection and mapping application was done by Ustin (2002) and Underwood (2003) in California's Mediterranean ecosystems. In their studies, several classification methods were investigated and compared: (1) continuum-removal, (2) MNF, (3) band ratios, and (4) SAM each with different justification and consideration. The first one was used to pick up the water absorption features in the spectrum, while the second approach took advantage of the information in full image spectrum and still able to reduce the dimensionality of the hyper-bands.

The third method was selected on the basis that band ratio is very sensitive to biochemical and biophysical properties of vegetation, and the last approach took advantage of the dimension of the hyperspectral dataset to come up with an angle measurement plotted in the multi-dimensional space by each individual vegetation spectrum. The accuracy was very high although it varied over different test sites. Other advanced approaches have been previously explored. Vrindts, et al. (2002) developed a statistical approach toward invasive species detection. Fitzgerald (2004) applied the Spectral Mixture Analysis (SMA), also called linear un-mixing approach, to de-correlate each pixel into several basic components to enhance classification accuracy.

The temporal consideration in hyperspectral remote sensing was also discussed by Dennison (2003) in which he found that there was a negative correlation between the increase of non-photosynthetic vegetation (NPV) and soil water balance decrease. He also reported that variation in water deficit image resulted in large confusion in classification. A larger number of endmembers were suggested to enhance the classification accuracy while the seasonal variation in the spectral response should be taken into account in vegetation classification. Among these studies the MNF or MNF combined approach yields very good result in crop mapping. The MNF approach is also utilized in this thesis research.

### **Hyperspectral data analysis**

Hyperspectral data analysis can be divided into two categories (Aspinall 2002). One is top-down, which essentially uses field maps to train the imagery so as to detect certain features of the examined objects. Field survey and geo-referencing are necessary because high positioning accuracy is needed in this approach. Atmospheric correction of the imagery may not be needed in this approach. Since the high spatial resolution image usually does not have large

extent coverage, the atmospheric variation within each scene is not noticeable. Associating the ground features directly with the image will enable the classifying algorithm to incorporate atmospheric effects into the feature spectra to search for similar features on the same image. This approach is not feasible for large physical extent analysis (Aspinall 2002).

The other approach, in contrast, is bottom-up which typically uses ground- or lab- measured spectral libraries to identify features in the image. Atmospheric correction is essential because atmospheric effects have to be removed from the image before it can be quantitatively compared with ground-measured spectra (Kruse 1994). Geo-referencing and registration are necessary to match geographic positions of image pixels to ground sites. To reduce spectral noise, the absorption regions such as affected by water and carbon-dioxide of the spectrum should be removed before further processing.

### **Atmospheric correction**

Removing atmospheric effect involves calibration and atmospheric correction. Calibration adjusts the image by converting raw radiance values of each pixel to top-of-atmosphere absolute (radiance) or relative (reflectance) values. Atmospheric correction then adjusts these values to ground radiance or reflectance at each pixel based on sun-ground-sensor geometry and atmospheric composition. In general the approaches of hyperspectral atmospheric correction could be divided into three categories: (1) Scene-Based Empirical Approaches, (2) Radiative Transfer Modeling Approaches, and (3) Hybrid Approaches (Gao 2006).

#### *Scene-Based Empirical Approaches*

During the mid-1980s, several scene-based empirical approaches were developed to remove atmospheric effects from hyperspectral image and to derive surface reflectance spectra. Among these methods, flat field calibration (Goetz and Srivastava 1985; Roberts et al. 1986) and internal average relative reflectance (IARR; Kruse et al. 1985; Kruse 1988) could produce relative reflectance spectra. Flat field calibration utilized a known area of reflectance on the image, usually defined as a Region of Interest (ROI), to normalize the raw radiance.

The radiance spectrum from this area is assumed to be resulted from pure atmospheric effects. It is then used as normalization factor to divide the raw spectra at each pixel of

the image. The resultant ratio is the relative reflectance and could be compared with laboratory spectra. The IARR Calibration technique is used to normalize images with a scene average spectrum.

This calibration method is performed by calculating an average spectrum from the entire scene which is used as a reference spectrum. The apparent reflectance is then calculated by dividing the reference spectrum with the pixel value. This technique is often used to convert imaging spectra to relative reflectance when ground spectral measurement is not available. It works best in arid areas with limited vegetation cover.

#### *Radiative Transfer Modeling Approaches*

Surface reflectance can also be derived from hyperspectral images using Radiative Transfer Functioning (RTF) approaches (Gao 2006). The Atmospheric Removal Program (ATREM; Gao and Goetz 1990; Gao et al. 1993) is a RTF-based calibration method to calculate absolute reflectance that requires no ground-based measurement.

This method was first developed for airborne AVIRIS imagery that has 224 bands. It uses water absorption bands to calculate the amount of water vapor atop of each pixel. This information is then used to calculate surface reflectance in the Simulation of Satellite Signals in the Solar Spectrum (5S) model (Tanre 1990). Other RTF models such as MODerate resolution atmospheric TRANsmission (MODTRAN) can be used to in this process to calculate surface reflectance (Berk et al. 1998).

More atmospheric correction algorithms for retrieving surface reflectance include the Atmospheric CORrection Now (ACRON; Berk et al. 1999), and the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH; Adler-Golden et al. 1999). Some approaches include more advanced features, such as spectral smoothing, topographic correction, and adjacency effect correction (Gao 2006).

#### *Hybrid Approaches*

The atmospheric correction methods mentioned above are isolated approaches, and each is tailored to specific conditions. A combination of those methods sometimes can yield good results. For example, Clark et al. (1995) used a combination of ATREM and empirical line method to correct model errors in ATREM by calculating normalization factors of each pixel and then apply them to the ATREM corrected image. Some methods take advantage of ground measurements and MODTRAN to derive an equivalent model of empirical line method which has loose requirement

on the uniform ground targets of different reflectance (Goetz et al. 1998).

The best among these methods is the Empirical Flat Field Optimal Reflectance Transformation (EFFORT) that bootstraps a linear adjustment to apparent reflectance spectra to improve the accuracy (Goetz et al. 1997; Boardman 1998). The advantage of this method is that it improves the comparability of the corrected reflectance spectra with library-based spectra.

#### *Data collection considerations with various atmospheric correction schemes*

Field data may or may not be needed in atmospheric correction of hyperspectral images, depending on the analysis that will be utilized (Aspinall 2002). The IARR method requires no field data, which eliminates field data collection efforts at the expense of accuracy. The ATREM also does not need field data but is more accurate than IARR because it does require the sensor capability to capture narrow band width, especially in water vapor absorption bands. Flat field calibration only requires spectral data from one homogeneous site. Empirical line method requires a minimum of two high-contrast ground references sites although more references sites is preferable. MODTRAN requires extensive ground-based measurements and the information of atmospheric components, thermal structure and water content at different levels.

### **Geometric Corrections**

Because the altitude of a flying plane is low enough to be affected by air currency, it is a challenge to keep the imaging platform steady. Image quality is not comparable to that of satellite platforms (Tong, et al. 2004). As a result airborne remote sensing imagery needs to be geo-rectified and registered to ground control points (GCP).

This approach is expensive and time consuming due to the number of GCPs (Tong, et al. 2004). Most recent and advanced geometric corrections include Position and Orientation System / Direct Georeferencing (POS/DG; Reid, et al. 1998) supported by Global Positioning Systems (GPS) and Inertial Navigation Systems (INS) aboard the airplane. The combined system could provide information such as absolute position (x, y, z) and platform attitude parameters, which make it possible for real time geometric correction of airborne images using ray tracing to establish the relationship between the pixel and its ground counterpart.

Geometric correction is not necessary in this research for several reasons: (1) the weather on the image acquisition date was very pleasant which will ensure a more stable flight and good imaging quality, (2) the elevation in the research area is relatively stable, only a few meters difference negligible as compared to the flying height of the platform, (3) The image used in this research was geo-corrected with a C-Migits III GPS/INS unit manufactured by Systron Donner (CHAMP 2006). The system records GPS and aircraft attitudinal positions (roll, pitch, yaw, speed and heading). The rectification process uses the GPS and INS inputs to generate a global lookup table which is applied to the uncertified image (Tong, et al. 2004). The hyperspectral image matched very well with geo-orthorectified digital airphotos (DOQ).

### Mapping and classification

Hyper-spectral imagery presents numerous possibilities for interpretation and analysis (Aspinall 2002). A lot of sensors have been developed which can provide a near complete spectrum for each pixel using high spectral resolution. Calibrated hyper-spectral data is comparable to laboratory spectra to identify ground materials at pure or mixed pixels. There are a number of specialized approaches tailored to hyper-spectral dataset that extract unique spectral features of different materials. Analysis of hyper-spectral imagery usually requires an empirical match between image spectra and reference spectra (end-members) from either a spectral library or field measurements.

#### Band ratio

Band ratio can be used to capitalize the spectral difference between different objects (Vincent 1997) to support the classification. Band ratios such as Normalized Difference Vegetation Index (NDVI) and Soil-Adjusted Vegetation Index (SAVI) have been defined in the literature to highlight vegetation properties (Elvidge and Lyon 1985; Huete et al. 1985; Huete 1988). The use of ratios also removes shadow effects caused by different angles of surface illumination. In multispectral remote sensing vegetation indices often use broad-wavelength red and near-infrared bands, such as Band 3 and 4 in Thematic Mapper (TM) images. Due to enormous pool of bands available in hyperspectral remote sensing, band selection is necessary before band ratio could be utilized.

Many approaches have been developed to select optimal bands in hyperspectral remote sensing images. Ifarraguerra (2004) measured a specific distance to all bands and then displayed the distances in image histogram to visually pick up optimal best bands. Huang (2005) applied a more

complicated band selection using feature weighting. It was based on the matrix coefficient analysis to assign weights to original bands then to select the bands with the largest weights. Keshava (2004) developed Band add-on (BAO) approach to exploit a mathematical decomposition of SAM to incrementally select optimal bands.

#### SAM

The Spectral Angle Mapper (SAM; Kruse et al. 1993) matches pixel spectra to reference spectra using a similarity measure of angle, formed by the vectors of spectra in an n-dimensional space where n equals to the bands of image (Figure 2-2). In the SAM approach a smaller angle indicates a closer match. It is an exhaustive measure that compares each pixel vector with all available end-members and then classifies the pixel as the material with the smallest angle. The advantage of this approach is that it is insensitive to effects of illumination and albedo since only the angle between the vectors are measured instead of the length of them.

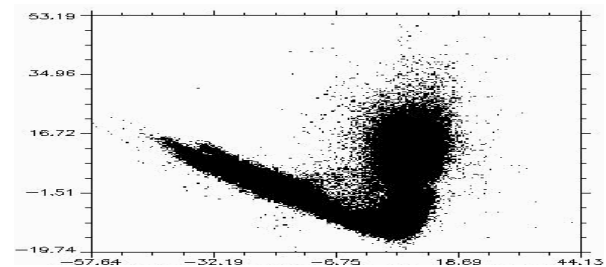


Fig 2: SAM algorithm illustration plot (ENVI 2002)

#### MNF and MTF

Minimum Noise Fraction (MNF) was first introduced by Lee et al. (1990). This algorithm was developed to improve the principal components transformation's inability to reliably separate signal and noise components in multi-band images. The MNF was derived as an analogue of the principle components transformation which, instead of maximizing the variance of the data, maximizes the noise content of each component. Then it is reversed to obtain maximum signal-to-noise ratio (SNR) of each component.

It is equals to transforming original data using noise covariance matrix as the identity matrix, followed by a principle component transformation (Lee, J. B. et al. 1990). Mixture-Tuned Matched Filtering (MTMF) does not require the knowledge of all the endmembers. It maximizes the

response of a known endmember and suppresses the response of the composite unknown classes (background) to match the known signatures (Chen and Reed 1987; Stocker et al. 1990; Yu et al. 1993;

Harsanyi and Chang 1994). This approach is similar to un-mixing, but it does not require heavy computation as well as the knowledge of all the endmembers. This approach may introduce high commission error for pixels that are rare in the image (ENVI 2002).

MTMF is a hybrid method based on both signal processing and linear mixture theory (Boardman 1993). It combines the advantage of both the Matched Filter method explained above and physical constraints imposed by mixing theory to reduce commission error (Boardman 1993). MTMF results are presented as two sets of images, the Matched Filter image (MF) and the Infeasibility images with values from 0 (no match and feasible) to 1 (perfect match and infeasible). These results give a way to estimate relative degree of match to the reference spectrum and the Infeasibility image, where a high MF score and low infeasibility score represents a good match (ENVI 2002).

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