

# DETECTION OF CANNABIS PLANTS BY HYPER-SPECTRAL REMOTE SENSING MEANS

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## ABSTRACT:

The dramatic increase of drug use, mostly hashish and marijuana, reinforces the demand for drug prevention and the need for accurate and updated information on cannabis fields. This study sought to evaluate the ability of Hyperspectral spectroscopy to discriminate cannabis from different scales and land use. The study was conducted in three stages: 1) Examination of the cannabis spectrum under laboratory controlled conditions from a short distance with field spectrometer and Hyperspectral camera under artificial light; 2) Remote sensing of the cannabis from an oblique view using static imaging spectrometer from 25m and 80m; and 3) Airborne Hyperspectral pushbroom sensor (AISA Eagle 400-1000 nm). This method of down/up scaling was found to be useful in understanding the meaning of spectral discrimination. Results of Principal Component Analysis (PCA) show that the spectral signal of cannabis (leaf and canopy) varied with distance from the sensor, however spectral bands with the most influence are in the range of 530-550, 670-680 nm and 705-720nm.

## 1. INTRODUCTION

Drug use, mainly of hashish and marijuana, has dramatically increased over the past decade. Drug prevention reinforces the need for accurate and updated information on cannabis fields. The demand for monitoring and detecting large areas of drug-oriented plants (e.g. cannabis) is increasing accordingly. Remote Sensing (RS) technology, with low spectral resolution such as SPOT 5, can be used for cannabis discrimination (World Drug Report, United Nation, 2006). However, this method is useful for very large agricultural areas and not for small fields, in which accurate high spectral resolution is needed. The spectral feature of vegetation (leaf, canopy) can be a useful tool for separation of vegetation at the species

level (Cochrane, 2000; Vrindts *et al.*, 2002). The factors that influence the spectral signal for the discrimination are not well understood. Leaf geometry, light scattering, noise factor and type of sensors have the most influence on the leaf/canopy reflectance signal (Cochrane, 2000; Okin *et al.*, 2000). Hyperspectral technology, which is defined as the simultaneous acquisition of images in many narrow, continuous spectral bands (Schmidt and Skidmore, 2000) was found useful for studying the biochemical components of vegetation (Asner, 1998). In this study, we hypothesize that very high spectral resolution data can discriminate between cannabis plants and surrounding vegetation in different land uses. The aim of the study is to check this assumption.

## 2. MATERIALS AND METHODS

### 2.1 Plant Preparation

Plants of *Cannabis Sativa* were sown and grown in the greenhouse of the Botanical Garden at Tel Aviv University for three months up to 0.3 m high. To create a mixed neighborhood, fifteen cannabis plants were mixed with weed and tree species for hyperspectral acquisition.

### 2.2 Remote Sensing Hyperspectral (HS) Methods

In this study a Field Spec®Pro Spectrometer (Analytical Spectral Device (ASD), Inc., Boulder, Colorado, USA) with a fiber-optic contact probe was employed for laboratory measurements and an optical fiber with a field view of 25° was employed for field measurements. In addition, two different Hyperspectral cameras were used for better spectral and spatial understanding of reflectance data in the canopy scale. Table 1a describes the technical features of each camera. For observations 500 m above the ground an Airborne Hyperspectral Sensor with 400 spectral bands in the range of 400-1000 nm was used (Table 1b).

### 2.3 Spectral Measurements - Data Acquisition

#### 2.3.1 Laboratory - Field Spectrometer Measurements

Besides the cannabis plants the reflectance measurements of leaves of six vegetation species were acquired. These six species represent Mediterranean trees, agricultural crops and wild plants that grow in Israel (Table 2). For each species 40-150 spectral measurements were collected. Three spectra were collected for each sample, and the average of these three samples was used for later analysis.

#### 2.3.2 Hyperspectral Camera and Air Sensor Acquisition

To create a mixed neighborhood, the cannabis plants were mixed with two other vegetation species, citrus and weeds. The acquisition was done from 1m distance in the laboratory, from 25 m and 70 m above the ground. The data acquisitions were achieved by two spectral cameras presented in Table 1a.

IFOV milliradians	FOV°	Spatial resolution	Spectral resolution (nm)	Number of bands	Camera
none	Depending on focal angle	0.6 From 1000 m height	6-10	60-180	ASI COOL-1300/Q
0.029	29.9	0.5-1.2 From 1000 m height	2.9	488	AISA EAGLE Ground detector

Table 1a. Technical features of HS cameras

IFOV milliradians	FOV°	Spatial resolution	Spectral resolution (nm)	Number of bands	Camera
0.029	29.9	0.5-1.2 From 1000 m' height	2.9	488	AISA EAGLE Airebore detector

Table 1b. Technical features of AISA Airborne

Species	Number of Spectral Samples	Study Area
<i>Cannabis Sativa</i>	150	Tel Aviv University Botanical Garden
<i>Quercus calliprinos</i>	50	Tel Aviv University Botanical Garden
<i>Citrus</i>	100	Ruppim Institute
<i>Arbutus andrachne</i>	50	Tel Aviv University Botanical Garden
<i>Quercus boissieri</i>	50	Tel Aviv University Botanical Garden
<i>Avena sativa</i>	40	Tel Aviv University Botanical Garden
<i>Gossypium barbadense</i>	50	Kibuz Revadim
<i>Solanum lycopersicum</i>	50	Emek Izrael
<i>Quercus</i>	50	Tel Aviv University Botanical Garden

Table 2. Vegetation species that were used for laboratory spectral library

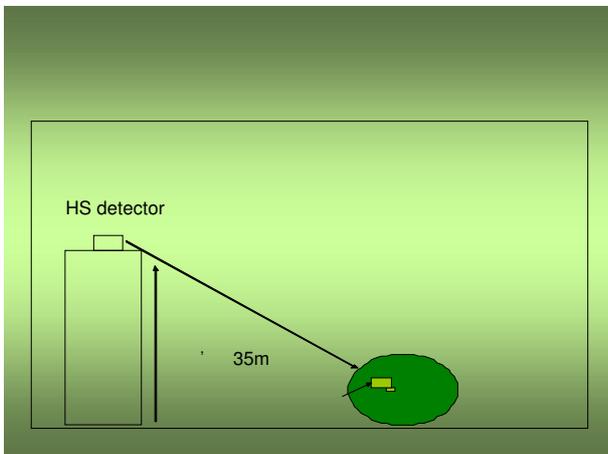


Figure 1. Ground Hyper-Spectral Acquisition Set Up

### 2.3.3 Airborne Hyperspectral Data acquisition

The AISA Eagle Hyperspectral sensor (400 bands) was used to detect *Cannabis Sativa* fields under clear and well known climatic conditions over cotton fields. The acquisition took place near Kibbutz Revadim, in the south of Israel, from heights of 500 m (1500

ft). The pixel size was around 0.3 m and the signal to noise ratio 450.

## 2.4 Data Preprocessing

### 2.4.1 Laboratory Data from Field Spectrometer

Spectral samples, mostly leaves of each vegetation species (Table 2), were included in a reference spectral library. For each species we created reference spectra that represented the average of five different spectral measurements. Each spectral sample was divided by the reference spectra to test the similarity. Bad spectral samples, i.e. ratio below 0.9 were eliminated from the spectral library. This method minimizes errors related to bad calibration.

### 2.4.2 Ground Hyperspectral Data

The data from the Hyperspectral sensor was converted to reflectance by using the EL (Empirical Line) calibration method. Spectral reflectance of four artificial gray-scaled targets was collected *in-situ* and used for the EL correction. Spectral libraries of vegetation species from each acquisition were also generated for later analysis .

## 2.5 Data Analysis and Spectral Transformation

Spectral libraries data were exported to the Unscrambler software (Unscrambler Software, v9.1 CAMO 1986-2004) for statistical and mathematical manipulation. Spectral data was reduced from 480 to 120 bands in the first run and 68 spectral bands in the second run by manual selection of the most informative wavelengths (Siesler, 2002). Then, the smoothing filter by Savitzky and Golay was applied to remove remaining noise in the data. Thereafter, the first derivative values of the reflectance data underwent PCA. The chemistry arguments are based on the biochemical and biophysical components of leaf, i.e. Chlorophyll *a* and *b*, Anthocyanins that have specific spectral components at approximately 530-750nm (Asner, 1998; Blackburn, 2006). Additionally we used a

Spectral Linear Unmixing (SLU) method. Briefly, the SLU deconvolution technique takes an airborne spectrum into several pure End-Members (EM) derived from a laboratory pure plant spectral library. The EMs were of cannabis spectra, Cotton and Soil spectra.

### 3. RESULTS

#### 3.1 Spectral Analysis

The first derivative analysis of laboratory spectral measurements of leaves from several vegetation species and *Cannabis Sativa* plants in the spectral range of 700-730 nm (Red Edge) shown that cannabis exhibits a spectral shift towards the shortwave (to the left) mostly compared to: *Solanum lycopersicum* and *Gossypium barbadense* (Figure 2). The RE feature is used for remote sensing of specific locations on earth to identify plants species (Seager, 2005). Wavelength absorbencies at 530-550 nm, 670-680 nm (Chlorophyll absorbance) and 705-720 nm (RE) were found to be the most informative regions for cannabis identification (see further paragraph).

##### 3.1.1 Statistical Analysis

Figure 3 shows the results of the first two principal components (PC1 and PC2) based on data set measured by ASD (first derivative of reflectance). As can be seen, four groups can be identified: cannabis, crops, Mediterranean trees and citrus. The first component explains 76% and the second component explains 18% of the spectral variance accordingly. It was found that the wavelengths with the most effect on the variability of the two first PCA components are: 530-560 nm, 680-690 nm and 705-720 nm (RE). Furthermore, when PCA was run on the over acquisition, (25 m and 70 m), the classification shows that groups of similar species have similar spectral properties (data not shown) Figure 4 shows the two first PCA classifications of Hyperspectral acquisition from a distance of 1 m. The first component explains 87% and the second component

explains 7% of the spectral variance accordingly. The wavelengths that most affect the variability are identical to the wavelengths that were found in the laboratory results. However, in spite of a separation between three groups, a slight overlap can be observed between weed and citrus groups. We assume that this overlap can be related to the physical structure of the canopy that creates a diffused reflection (Bousquet *et al.*, 2005).

### 4. CONCLUSIONS

- 1) This study indicates that Hyperspectral imaging is a capable tool to distinguish cannabis plants from several surrounding vegetation types in different land uses
- 2) It was shown that spectral identification of cannabis plants can be done at different distance levels: from the laboratory to the ground and to the air.
- 3) The spectral results indicate that the cannabis plants have a different spectral signature in very narrow spectral bands, compared to other vegetation species. The best spectral identification region for cannabis plants was found to be at: 530-550 nm, 670-680 nm and 705-720 nm.

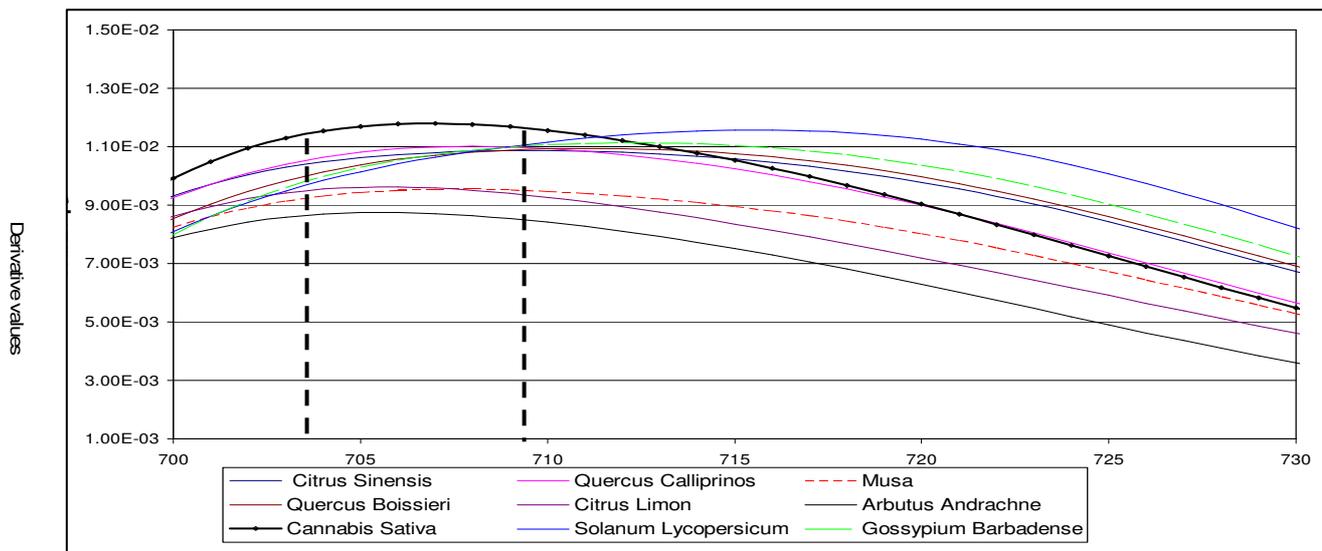


Figure 2. First Derivative of Cannabis Spectra and Vegetation Species

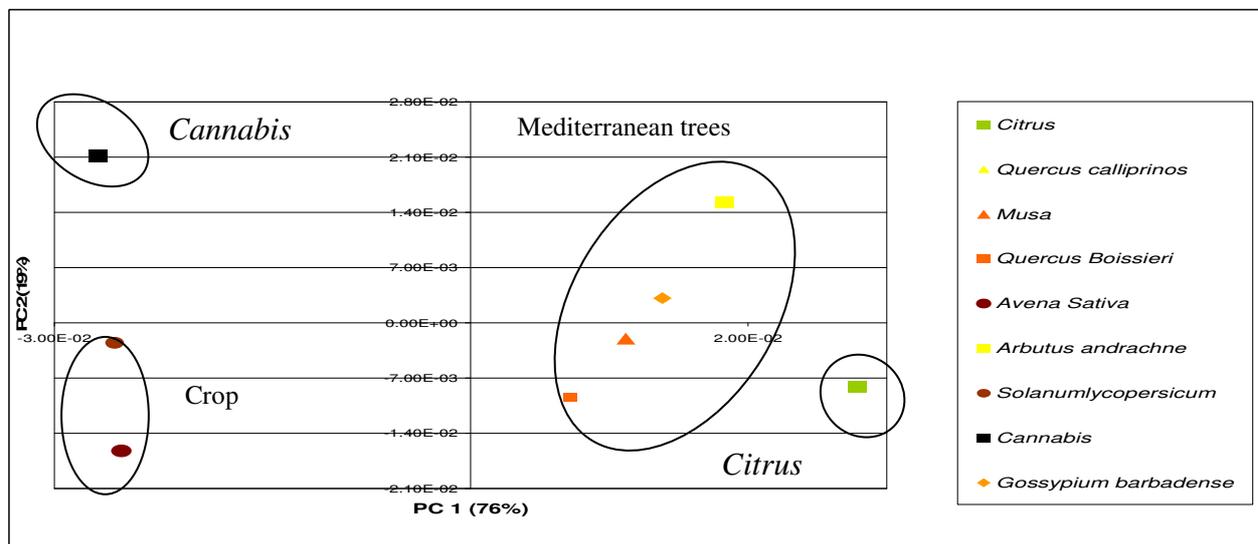


Figure 3. PCA of Spectral Library of Cannabis and over Vegetation Species.

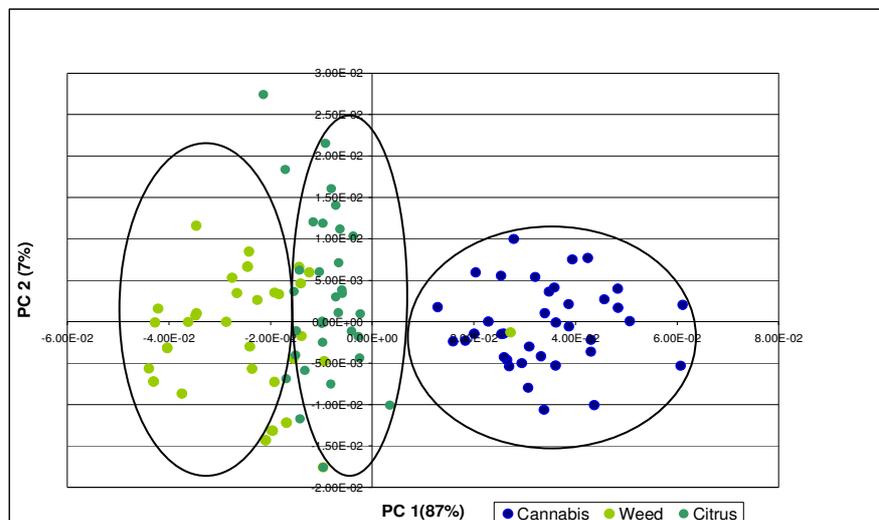


Figure 4. PCA classification from 1m

## **References**

Asner, G. P. (1998). "Biophysical and biochemical sources of variability in canopy reflectance". *Remote Sensing of Environment* 64(3) pp. 234-253.

Blackburn, G. A. (2007). "Hyperspectral remote sensing of plant pigments." *Journal of Experimental Botany* 58(4): 855-867.

Bousquet, L., S. Lacherade, et al. (2007). "Leaf BRDF measurements and model for specular and diffuse components differentiation (vol 109, pg 126, 2007)." *Remote Sensing of Environment* 109(1) pp. 126-126.

Cochrane, M. A. (2000). "Using vegetation reflectance variability for species level classification of hyper-spectral data". *International Journal of Remote Sensing* 21(10), pp. 2075-2087.

le Maire, G., C. Francois, et al. (2004). "Towards universal broad leaf chlorophyll indices using PROSPECT simulated database

and hyperspectral reflectance measurements." *Remote Sensing of Environment* 89(1): 1-28.

Schmidt, K. S. and A. K. Skidmore (2001). "Exploring spectral discrimination of grass species in African rangelands". *International Journal of Remote Sensing* 22(17) pp. 3421-3434.

Seager, S., Turner, E. L., Schafer, J. and Ford, E. B. (2005). "Vegetation's Red Edge: A Possible Spectroscopic Biosignature of Extraterrestrial Plants". *Astrobiology* 5(3) pp. 372-390.

Siesler, H. (2002). Introduction, general remarks. In: *Near-Infrared Spectroscopy: Principles, Instruments and Applications* (Siesler, H., Y. Ozaki, S. Kawata and H. Heise eds). WILEY-VCH, pp 1-12.

Vrindts, E., J. De Baerdemaeker *et al.* (2002). "Weed detection using canopy reflection". *Precision Agriculture* 3(1) pp. 63-80.

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