# A SOLUTION FOR THE MIXTURE PROBLEM IN AGRICULTURAL REMOTE SENSING

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## 1. INTRODUCTION

A common problem in agricultural remote sensing is the sub-pixel spectral contribution of background soils, weeds and shadows which impedes the effectiveness of spectral vegetation indices to monitor site-specific variations in crop condition [1]. To address this mixture problem, the present study combines in situ and hyperspectral data in an alternative spectral unmixing algorithm. The model driven approach, referred to as Soil Modeling Mixture Analysis (SMMA), combines a general soil reflectance model [2] and a modified spectral mixture model [3] providing as such the opportunity to simultaneously extract the sub-pixel spatial extent and spectral characteristics of crops. The robustness of the approach was extensively tested using a virtual orchard model [4] and in situ measured mixed pixel spectra from *Citrus* orchards.

## 2. SOIL MODELING MIXTURE ANALYSIS

In its most simple expression the mixed spectrum $r$ of soil and vegetation can be defined as:

$$r = r_{soil} \times f_{soil} + r_{vegetation} \times f_{vegetation} + \varepsilon \qquad (1)$$

where $r_{soil}$ and $r_{vegetation}$, $f_{soil}$ and $f_{vegetation}$ are the spectral signals and sub-pixel cover fractions of the soil and vegetation endmember, respectively. The portion of the spectrum that cannot be modeled is expressed as a residual term, $\varepsilon$. Equation (1) is the basis of the SMMA algorithm [1] which exists of several well defined steps as outlined below.

### 2.1. Soil Reflectance Modeling

The major part of spectral variation in soil spectra can be assigned to soil type (i.e., soil texture) and soil moisture content (SMC). Therefore, a general soil moisture reflectance model [2] was used to account for the pixel-by-pixel variations in $r_{soil}$:

$$r_{soil}^{*} = f \ + (1 - f \ ) \cdot e^{(-a \ \cdot SMC)} , \ r_{soil}^{*} = \frac{r_{SMC,soil}}{r_{soil,dry}} \ , \ f \ = \frac{r_{soil,sat}}{r_{soil,dry}} = \frac{1}{n_{water}^{2} \cdot (1 + r_{soil,dry}) + r_{soil,dry}} \cdot e^{(-\alpha \cdot l)} \qquad (2)$$

where $r_{soil,SMC}$, $r_{soil,dry}$ and $r_{soil,sat}$ are the reflectance of the soil for a specific SMC, in dry and in saturated condition, respectively. $a$ is the attenuation factor while $\alpha$ is the absorption coefficient of water. $l$ is the active water layer thickness of the soil.

### 2.2. Spectral Mixture Analysis

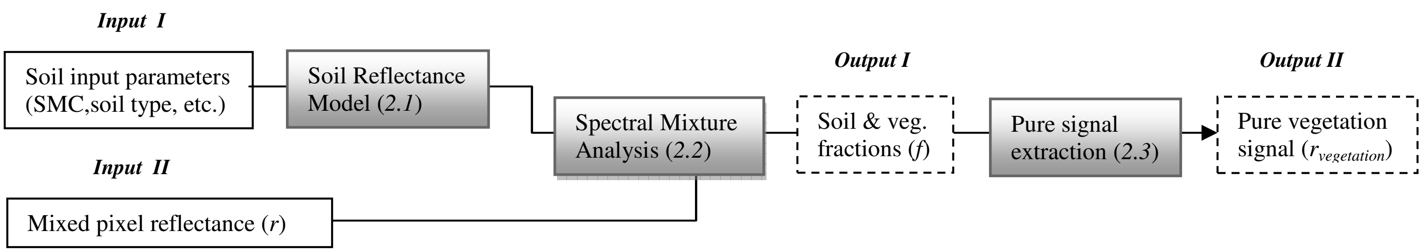
Traditionally, Spectral Mixture Analysis (SMA) involves the definition of standard (image-wide) endmember spectra. Sub-pixel endmember fractions are estimated by optimization of $f$ in such a way that the residual error $\varepsilon$ in Equation (1) is minimized. In SMA, the accuracy of fraction estimates linearly decreases with both the variability within and the similarity among endmember classes [5]. To reduce this effect an automated waveband selection protocol is used to select the set of wavelengths that are least sensitive to endmember variability [3]. The selection is based on a minimum instability index (ISI) criterion [6]. ISI is defined as the ratio of the spectral variability within (i.e., the sum of the one-sided 95% confidence interval per endmember class) and the spectral variability among the endmember classes that are present within the mixture (i.e., average euclidic distance between the class means). This approach, referred to as Stable Zone Unmixing [3], allows to only use the "stable" spectral zones in the unmixing algorithm, providing improved cover fraction estimates.

### 2.3. Extraction of pure vegetation spectra

The soil reflectance model described in *2.1.* is used to estimate $r_{soil}$. The Stable Zone Unmixing approach described in *2.2.* is used to estimate the sub-pixel cover fractions of soil and vegetation ($f_{soil}$, $f_{vegetation}$). Consequently, the pure vegetation spectrum can easily be extracted from Equation (1), as it is the only remaining unknown:

$$r_{vegetation} = \frac{r-(r_{soil}\times f_{soil})}{f_{vegetation}} + \varepsilon \qquad (2)$$

A schematic overview of the Soil Modeling Mixture Analysis approach is given below:




## 2. CONCLUSIONS

Preliminary results of SMMA have been presented in [1]. Synthetic mixtures, i.e., compiled from in situ measured hyperspectral bare soil and *Citrus* tree canopy spectra, were decomposed and the sub-pixel crop cover fractions ($R^2 > 0.94$, RMSE < 0.03) and pure vegetation signals (average extraction $\text{error}_{350 \text{ to } 2500} = 0.017$, RMSE = 0.02) were adequately extracted from the mixtures. The SMMA approach can be considered very promising. Therefore, ongoing research is testing the robustness of the approach in a varying set of scenarios using a virtual orchard model [4]. The effect of weeds, shading, illumination and atmospheric conditions, multiple scattering, etc. can as such carefully be controlled and studied. Results will be further validated using real in situ measured mixed pixel spectra from *Citrus* orchards. The results of this analysis will be presented on the symposium.

## 3. REFERENCES


[1] Somers, B., Delalieux, S., Verstraeten, W.W., et al., "A conceptual framework for the simultaneous extraction of sub-pixel spatial extent and spectral characteristics of crops", *Photogrammetric Eng. & Remote Sens.*, 75, 57-68, 2009.

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