

# ESTIMATION OF SURFACE SOIL ORGANIC MATTER BY MEANS OF HYPERSPETRAL DATA ANALYSIS.

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## ***Abstract***

Data acquired from field campaign and hyperspectral airborne sensors were processed to determine the surface soil organic matter of an agricultural area located in Southern Belgium. The method adopted was based on a forward stepwise multiple regression analysis linking soil organic matter and hyperspectral data from two airborne sensors working in the visible and infrared domain. The results were validated successfully from an independent set of sampling points. It is concluded that the hyperspectral remote sensing approach is promising for soil organic matter prediction. Furthermore, this approach could even be improved if disturbance factors are removed.

**Keywords:** Soil Organic Matter, Hyperspectral Remote Sensing, Agriculture, Southern Belgium.

## ***1- Introduction***

Hyperspectral remote sensing (HRS) has gone through rapid development over the past two decades in agriculture and environmental related applications [1], [2], [3]. Among these applications, the estimation of soil organic matter (SOM) appears as a very promising one as it may provide new information on the spatial variability of this important agricultural factor of production. But soil is a complex system and its properties cannot be easily assessed even under controlled laboratory conditions [3]. It is even more complicated under remote sensing condition. In fact, extracting reflectance values from a HRS pixel is an uneasy task due to illumination and terrain changes, atmospheric attenuation and low signal-to-noise ratio. On the other hand, soil is a more heterogeneous material than vegetation, which results in greater difficulties in applying quantitative analyses to HRS soil data. However, several studies for analysing SOM properties from HRS have been performed [4],[5], [6], [7]. Ben-Dor and Banin [3] have shown that the HRS approach is useful for assessing SOM properties if careful spectral manipulation techniques are used. Moreover, they showed that for several soil properties, a large number of channels is not always required to accurately predict SOM.

This paper investigates the application of HRS for the estimation of the SOM in the context of precision farming. This approach has never been applied to the agricultural environment in Belgium. The correlations between field SOM measurements, obtained by laboratory analysis, and soil reflectances derived from one operational (Compact Spectrographic Imager – CASI-2) and one experimental (Shortwave Infrared Airborne Spectrographic Sensor – SASI) hyperspectral data will be analysed.

## ***2- Materials and methods***

### **2-1 Study site and ground measurements**

The area selected for this study (50 km<sup>2</sup>) is located in Southern Belgium (49°38'; 49°43' N and 5°27'; 5°31' E). This area is typical of agricultural practice in this part of Belgium with a mixing of meadows and fodder maize with cereal crops. The zone was selected because of its high variety of soils that provides a large range of SOM. Fourteen agricultural parcels with

bare soil were selected with about 10 soil samples locations per parcel leading to 135 soil samples. Five teams collected soil samples and measured field spectra during the day of flight. The soil samples were stored in plastic bags and brought into laboratory for chemical analyses and spectra were collected with a portable spectrometer (Analytical Spectral Devices or ASD). Each target area was described in detail and accurately georeferenced using GPS (Garmin, GPSMAP 76S) and DGPS (Leica 530, L<sub>1</sub>/L<sub>2</sub>, 10 Hz) devices.

## 2-2 Hyperspectral data acquisition and pre-processing

SASI and CASI sensors were mounted onboard a Dornier 228 aircraft from the UK Natural Environment Research Council (NERC) that flew over the sites during a sunny day (12/09/02) at an altitude of 1500 m, providing a pixel size smaller than 2.5 m x 2.5 m. The images, atmospherically, radiometrically and geometrically corrected, came from VITO. Nevertheless, there remained still small problems of geometry with SASI images that were solved by image-to-image registration with CASI images on ENVI environment. Spectral signatures of all the soil sampling location were then extracted. In a parallel procedure, all the soil samples were also measured for their reflectance in laboratory conditions (Département de Production Agricole, Gembloux) across the 400-2500 nm spectral range.

## 2-3 Laboratory analyses

The SOM content was determined by loss-on-ignition [8], [9]. Soil samples were weighted before and after a 24h drying into an oven at 105°C [10]. These analyses were performed by the Laboratoire des Ressources Hydriques at the Fondation Universitaire Luxembourgeoise (FUL).

## 2-4 Methodology of analysis

First, SOM provided by laboratory analyses was statistically studied. Then, the hyperspectral signals obtained by three different techniques (field measurements with ASD, signal measured by plane and measured in the laboratory) were compared for the same points to see the coherence of their response.

The next step consisted in making an analysis by a forward stepwise multiple regression on the various spectral bands. Out of this analysis, were extracted the bands with the best correlation to SOM and established a linear relationship following:

$$V_p = A_0 + A_1R_{\lambda_1} + A_2R_{\lambda_2} + \dots A_nR_{\lambda_n}$$

where  $V_p$  is the predicted value,  $A_0$  is a constant,  $A_i$  are the coefficients of the reflectance  $R_{\lambda_i}$  in the wavelength  $\lambda_i$ . The equation of prediction is an empirical expression of the estimation of the content in SOM but it already gave good results in former studies ([3]).

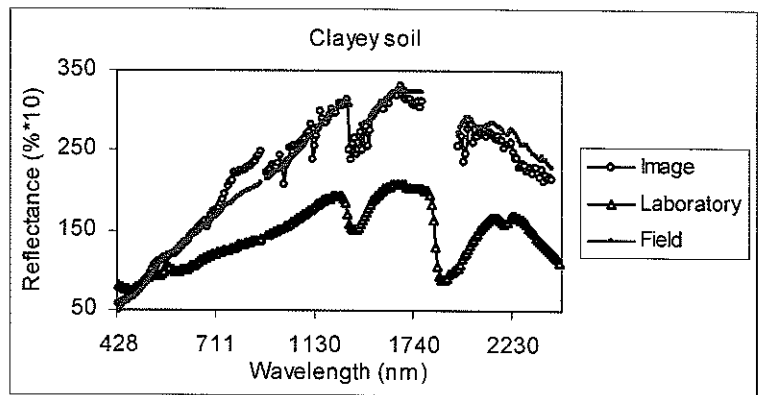
A statistical analysis and a classical calibration-validation procedure allow to judge the accuracy of this relationship. During this exercise, 2/3 of soil samples were used to calibrate the regression. The last third part served for the validation.

## 3- Results and discussion

Table 1 provides general information on the 135 soil samples selected in the 14 parcels of the area. These results come from laboratory analytical data and show that a wide range of SOM does exist (Min = 1.1; Max = 4.3). These results have quite different SOM as expected (large variety of soils from coarse sand to heavy clay). Another possible reason for such a large range of SOM might be due to remaining vegetation debris into the soil samples despite our efforts to eliminate all vegetation before laboratory analysis. SOM mean value is 2.2 % and stands in good agreement with previous studies [11]. The soil moisture content is also variable from site to site. In general, high SOM are found in areas with high soil moisture. In the present study, the coefficient of determination obtained between SOM and soil moisture is

relatively high ( $R^2 = 0.61$ ) and indicates that such a link might exist. This can be problematic because moisture affects CASI and SASI instruments outputs.

	Soil moisture content (%)	SOM (%)
Minimum	11,9	1,1
Mean	15,7	2,2
Sdt. Dv.	3,1	0,7
Maximum	31,1	4,3

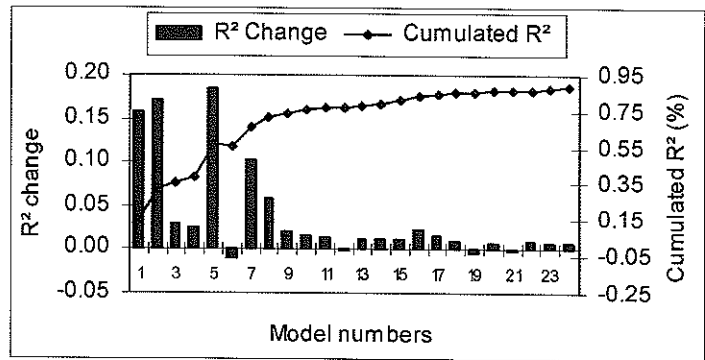


**Table 1: General information about the soil as obtained by lab analysis.**

**Figure 1: Comparison of spectra from laboratory, field and airborne images.**

Model	3	16
Variables	3 bands [850-2500 nm]	12 bands [400-2500 nm]
R	0.60	0.91
Std. Error	0.601	0.325
Sig.	** (p<0.05)	*** (p<0.01)

**Table 2: Statistical parameters of two representative models.**



**Figure 2: Cumulated and R<sup>2</sup> change values for stepwise produced models.**

In order to determine whether the spectral signatures given by laboratory, field measurements and remote sensing sensors are similar, these three signals were compared. Figure 1 presents the spectra of a clayey soil. As it can be clearly seen, the spectral signature from laboratory is lower than the others from 530 to 2500 nm. This can probably be explained by higher water content in the soil. In fact, the soil samples were taken on a 20 cm depth. The flying sensors and the ASD, which measure the soil surface reflectance (drier soil), give similar signatures except for CASI-2 sensor in the range of 730 to 950 nm. This is probably due to small inaccuracies in the wavelength and/or radiometric calibration (VITO team, pers. comm.). Others [12], [13] noticed the same problems.

The regression method presented in 2.4 was applied to 120 bands of both CASI-2 and SASI spectral data on 102 samples of SOM. The goal is to obtain the best correlation between the 120 spectral bands and the SOM given by chemical analysis. The same work was also done for the two sensors separately (not presented here). Doing so will reveal the ability of each sensor to predict SOM from its reflectance information.

In table 2, statistical parameters are provided for two typical models. The first model (3 variables) has all its 3 bands ( $R_{2010}$ ,  $R_{2299}$  and  $R_{930}$ ) situated in the SASI spectral region and is statistically significant (\*\*). Figure 2 shows the evolution of R<sup>2</sup> values for the different models and the contribution of each model. When adding more bands the R<sup>2</sup> value increases (e.g. for model 5 with 5 bands, the R<sup>2</sup> reaches 57%). This means that the model 5 can properly predict SOM with only five spectral bands. This result is in agreement with multi-spectral bands studies even if the band size is much larger in classical multispectral approaches.

The hyperspectral procedure, using much more channels, is well illustrated by the same figure. The precision of the models significantly increases with the number of bands. But for some combinations, this precision decreases (e.g. model 6). The model 16, performed with 12 bands, gives high predicted power (R-value = 0.91 and std. error = 0.32; see Table 2) and is statistically highly significant (\*\*\*). Besides this model, R<sup>2</sup> does not increase more than 5% even if the number of bands goes to 16. Actual SOM values and predicted values by model 16 are presented on figure 3. It appears that an excellent relationship occurs between the two set of data.

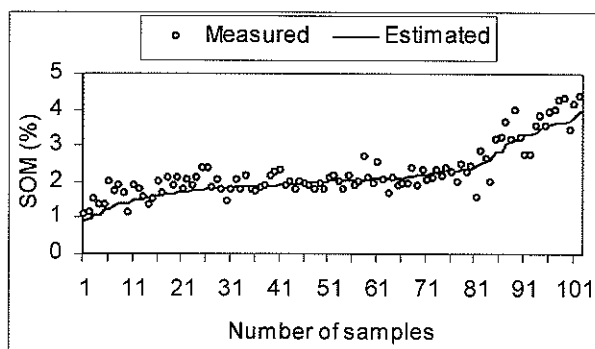


Figure 3: Measured and estimated SOM values.

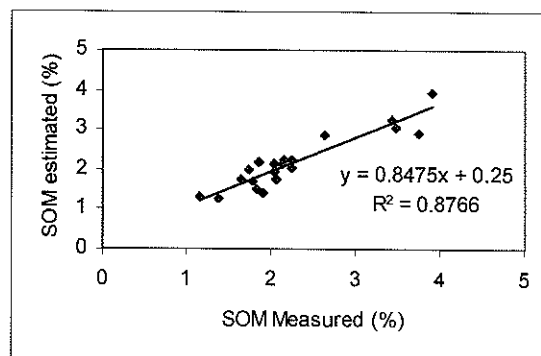


Figure 4 : Validation plot showing SOM actual values vs. predicted values.

Figure 4 illustrates the result based on a validation on an independent set of soil samples by using the above model. In this validation, spectra were extracted from SASI and CASI-2 images as indicated above. The predicted values are in good agreement with field values ( $R^2 = 0.83$ ). It should be noted that the prediction equation developed in this study is appropriate only for the area of investigation. But as this validation has been performed on a large area and on a great number of soil conditions, the current results do indicate that HRS method is an accurate tool for assessing surface soil organic matter.

#### *Conclusion and perspective*

This study shows a methodology to estimate the surface soil organic matter of agricultural parcels from hyperspectral remote sensing data. These preliminary results appear quite promising despite some disturbing factors (soil moisture and soil roughness variability, vegetation debris on the soil surface ...) not yet taken into account. A new APEX campaign in October 2003 will serve to study these factors more carefully.

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