Airborne Hyperspectral Measurements and Superficial Soil Organic Matter

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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 linear regression analysis linking soil organic matter and hyperspectral data from the CASI-2 (Compact Spectrographic Imager-2) airborne sensor working in the visible and near infrared domain. The results were validated successfully from an independent set of sampling points. However, disturbing factors effects are shown on the relationship between soil organic matter and spectral reflectance. It is concluded that the hyperspectral remote sensing approach is promising for soil organic matter prediction but it will require more study to better take account on the disturbing factors affecting the relationship.

Keyword: Soil Organic Matter, Hyperspectral Remote Sensing, Precision Agriculture, Southern Belgium

1 INTRODUCTION

Recent studies [1], [2] have shown the ability of the hyperspectral analysis in the field of precision farming. This technique allows the characterization of agri-environmental indicators and notably the estimation of certain terms of the nitrogen balance through the study of the soil organic matter (SOM) content and the chlorophyll content in plants. These two parameters, linked to the soil nitrogen concentration, intervene in the plant answer to fertilizer applications and are essential in the establishment of the nitrogen balance within the framework of precision farming. In spite of this, the nitrogen amount supplied by the SOM, which is far from being negligible in the balance, remains difficult to estimate. One of the reasons for this lies in the inter- and intra- variability of parcels SOM contents.

The main objective of this paper consists in determining the superficial SOM by means of hyperspectral data analysis. It aims also to continue the research begun during the APEX-2002 campaign, which showed very encouraging results [1]. In this 2002 preceding campaign, roughness, sparse vegetation (weeds) covering the soil surface, manure spreading, soil moisture content and soil types appeared as disturbing elements for the relationship between hyperspectral signature and SOM. This new campaign will investigate the impact of all these factors causing the degradation of the ‘hyperspectral surface signature- SOM’ relationship.

2 MATERIAL AND METHOD

2.1 Study Site and ground measurements

The area selected for this study (50 km²) is located in Southern Belgium (49°43'; 49°47' N and 5°42'; 5°46' 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. Ten agricultural parcels with bare soil were selected with 10 soil samples locations per parcel leading to 100 soil samples. During the day of flight, several teams collected soil samples, soil surface properties (roughness), soil moisture with a Theta-Probe and measured field spectra. The soil samples were stored in plastic bags and brought into laboratory for chemical analyses and spectra were collected with a portable spectrometer (Fieldspec Pro, Analytical Spectral Devices). Each target area was described in detail and accurately georeferenced using GPS (Garmin, GPSMAP 76S) device. A DGPS (Leica 530, L1/L2, 10 Hz) was also used for some points in order to control the GPS accuracy.

2-2 Hyperspectral data acquisition and pre-processing

The CASI-2 sensor was mounted onboard a Dornier 228 aircraft from the UK Natural Environment Research Council (NERC) that flew over the sites during a sunny day (10/15/03) 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. Problems of geometry were carefully checked and inaccuracy of two or three pixels was detected. So a window of 3x3 pixels was used to extract spectral signatures of all the soil sampling. In a parallel procedure, 20 soil samples, randomly selected from the initial set of soil data, were also measured for their reflectance in laboratory conditions (Vito imaging spectroscopy lab) across the 400-2500 nm spectral range with the same ASD spectrometer as in the field.

2-3 Soil chemical analysis

The SOM content was determined by loss-on-ignition [3], [4]. Soil samples were air dried (30°C) and sieved to remove small rocks, vegetated debris and coarse residues. Soil samples were weighted before and after a 24h drying into an oven at 105°C [5]. These analyses were performed by the Laboratoire des Ressources Hydriques at the Université de Liège, Campus d'Arlon.

2-4 Methodology of statistical 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.

In order to eliminate the noise, spectral bands were preprocessed using smoothing and derivative algorithms. The next step consisted in making an analysis by a forward stepwise multiple linear regression on the various spectral bands in attempt to determine wavelengths correlated with SOM. Out of this analysis, were extracted the bands with the best correlation to SOM and established a linear relationship following:

$$V_p = A_0 + A_1 R_{\lambda 1} + A_2 R_{\lambda 2} + \ldots A_n R_{\lambda n}$$

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 λ_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 [6], [7].

A statistical analysis and a classical calibration-validation procedure allow to judge the accuracy of this relationship according to Root Mean Square Error (*RMSE*) and Predictive Root Mean Square Error (*PRSME*) respectively for the calibration and validation phases:

$$RMSE\_and\_PRMSE = \sqrt{\frac{\sum_{1}^{n}\left(V_{fi} - V_{pi}\right)^2}{n-1}}$$

were V_{fi} and V_{pi} are the field and predictive values of SOM sample i respectively and n is the total number of samples.

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

The analytical results from laboratory data show that a wide range of SOM does exist on the study site (min = 0.6%; Max = 4.1% and mean = 2.0 %) as expected (large variety of soils from coarse sand to heavy clay). SOM mean value stands in good agreement with previous studies [1], [8]. 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 a typical spectrum from the three signals. As it can clearly be seen, the spectral signature from laboratory is lower than the others. This can be explained by the difference in illumination conditions and soil structure. The flying sensors and the ASD, which measure the soil surface reflectance at field conditions, give similar signatures except for some bands with the CASI-2 spectrum (near 769 and 950 nm). This is due to small inaccuracies in the wavelength as noticed by [9] and [10]. Figure 2 gives an example of the effect of some pre-processing on the airborne raw data. It can be noticed that the noise near 769 and 950 nm highlighted above disappears on the averaged smoothed spectra. Other disturbing factors such as atmospheric conditions are reduced by the derivative method. This method is also used to extract wavelengths with particular behavior.

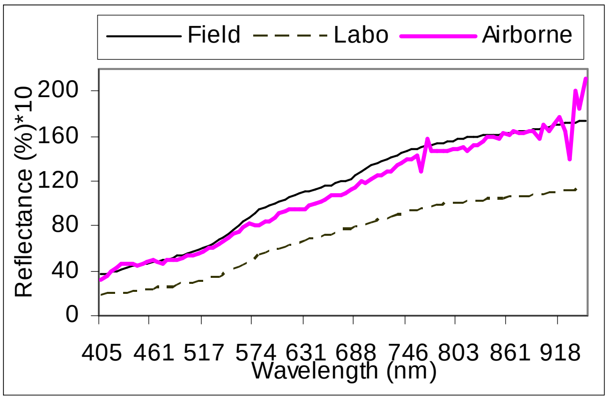

Figure 1: Typical spectra from laboratory, field and airborne images.

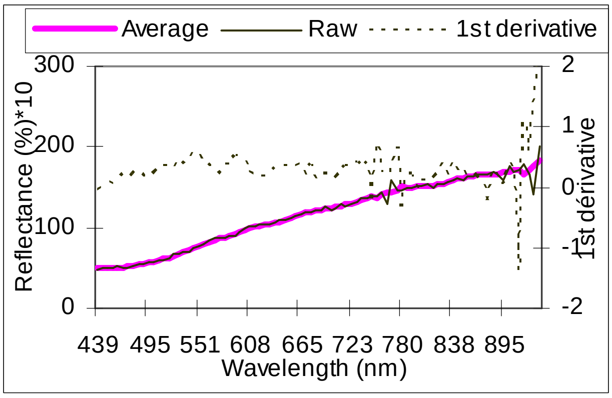

Figure 2: Example of effect of moving average window (size = 5 bands) and 1st derivative on spectra from airborne images.

The regression method presented in 2.4 was applied to 68 samples of CASI-2 from the Attert campaign using the SPSS, Statistic Software for Social Science, release 7.5 [11] . The goal is to obtain the best correlation between the spectral bands and the SOM given by chemical analysis. The same work was also done for the Tintigny previous campaign with 77 samples. The remaining data from each set (32 for Attert site and 39 for Tintigny site) will serve to validate the models. Doing so will reveal the ability of each set of data to predict SOM from its reflectance information and to verify if a model can be exported from one site to another.

In table 1, statistical parameters are provided for the best model on each site. Figures 3 and 4 illustrate the results based on validation with an independent set of soil samples by using the models obtained on the two sites.

Table 1: Statistical information about each site as obtained from the model simulation of SOM (%).

	Tintigny site (2002)		Attert site (2003)	
	Field data	Predicted data	Field data	Predicted data
Min	1.10	1.06	0.60	0.29
Max	4.30	4.02	4.10	3.74
Mean	2.28	2.28	1.99	1.99
St. deviation	0.78	0.74	0.97	0.89
CV(%)[a]	34	32	49	45
R^2	0.88		0.85	
ME(%)[b]	-0.003		-0.001	
RMSE	0.266		0.373	
n	77		68	

[a] CV(%) = Coefficient of Variation (St.Dev./Mean*100).
[b] ME(%) = Mean Error (mean difference between field and predicted values (%)).

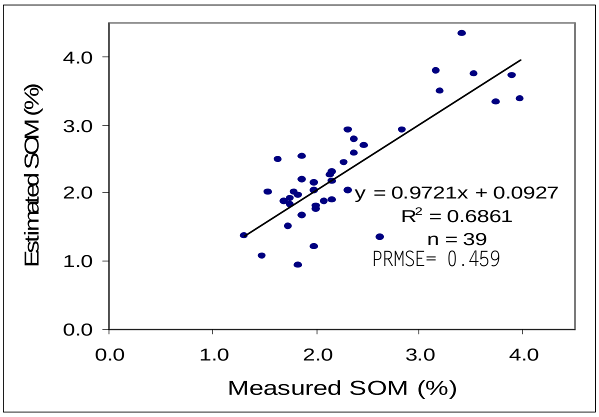

Figure 3: Validation plot of the SOM along the Tintigny site in 2002.

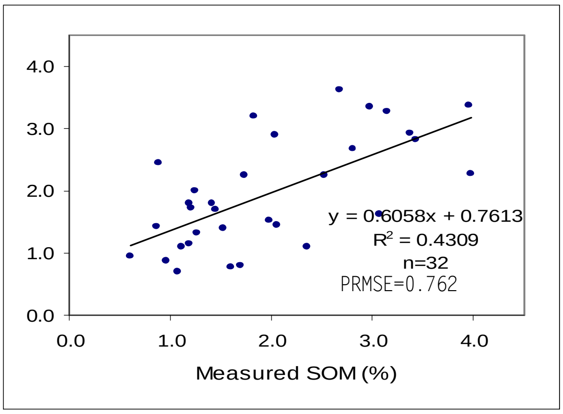

Figure 4: Validation plot of the SOM along the Attert site in 2003.

The predicted values are in good agreement with field values on the two sites. R² of Tintigny site and Attert site are 0.88 and 0.85 respectively. R² were greater than 0.80 denoting a reliable model for both sites. In fact, R² > 0.80 allows good quantitative prediction according to [12].The relative high CV(%) value on Attert site put into evidence that range of SOM is wider on this site. The very low absolute values of ME on both sites suggest that the stepwise procedure does not induce bias. The *RMSE* is lower on the Tintigny site leading to a better prediction than on the second site. This finding does not stand with the fact that the Attert parcels were selected to avoid disturbing factors such as vegetated debris or soil roughness. This point is discussed below.

The predictive power of the regression equations of the models characterized by table 1 is illustrated in figures 3 and 4 for the independent set of validation data. The prediction accuracy is better for Tintigny site with *PRMSE* = 0.46 vs. 0.76 on Attert site. This can be explained by the correlogramme shown in figure 5. In this figure, as well for the wavelength as for its derivative, the correlation coefficients are higher for the Tintigny campaign. This is probably due to the presence of vegetation debris on the soil surface in the 2002 campaign. It is obvious that vegetation is well correlated with the reflectance (see [13], [14], [15] or [16]). The correlogramme shown in the Attert site is in agreement with field ASD correlogramme (not presented). Such a result has been reported by [17] and [18]. An important aspect discussed by [18] is that variation in organic matter content can produce only a small change in the visible reflectance. As a result, poor correlation results can be obtained between CASI-2 reflectance and SOM as pointed out by [1]. But [1] obtained better results by combining CASI and SASI (Shortwave Infrared Airborne Spectrographic Sensor) data.

According to [19], the relationships between soil constituents and reflectance are geographically dependent and may not be easily extrapolated to other areas. This is confirmed here. Indeed, it should be noted that the prediction equation developed in this study is appropriate only for the area of investigation. Some attempt to use the models from one site to the other did not work well in the present study.

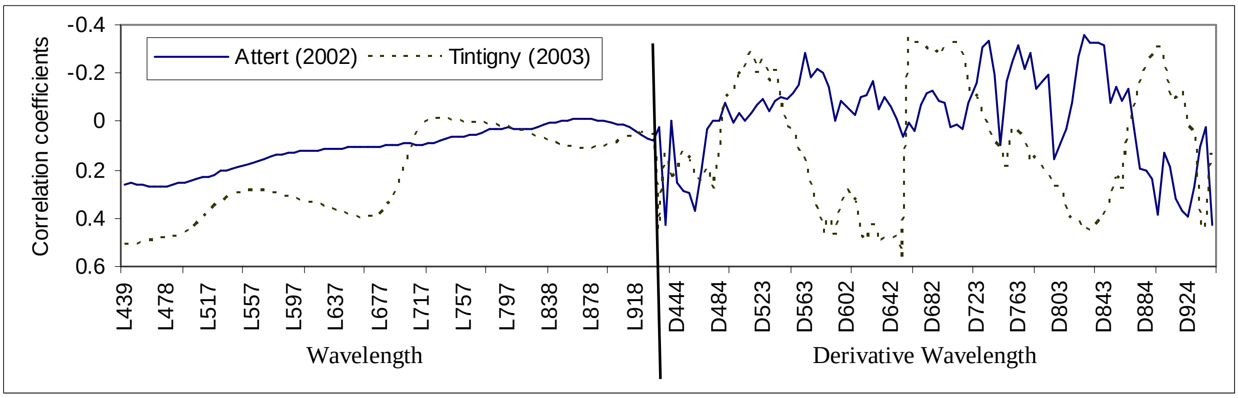

Figure 5: Correlogramme of the linear correlation between CASI-2 reflectance and its 1st derivative data and SOM on the Tintigny and Attert sites.

Data collected on these two sits give different results probably affected by the effects of natural soil surface conditions (e.g. color, roughness, moisture, vegetated debris, stoniness, etc.) or the influence of atmosphere on the illumination conditions (difference in sun-target-sensor geometry, Bidirectional Reflectance Distribution Function (BRDF), etc.). All these factors disturbing factors should be taken into account or at least those known to be the more important. In 2003, the effect of vegetated debris was negligible by selecting freshly ploughed parcels during the Attert campaign. The influence of natural soil roughness on reflectance has proven difficult to quantify [20]. This is due in part to the complex nature of agricultural soil surface but also to the lack of appropriate surface roughness measurements. In this study, we used an ingenious system capable of recording soil profile up to 0.25 m². The surface roughness measurements (SRM in mm) are represented as the standard deviation of the surface height variation. Figure 6 presents the correlogramme of SOM and SRM with a set of 13 samples. This figure shows a reflective effect between correlation coefficients of the two parameters. It can then be suggested that in the wavelength where correlation coefficient of SRM is high (hatched areas in fig. 6), the surface roughness will have more effect on the spectral signal and affect negatively the SOM estimation.

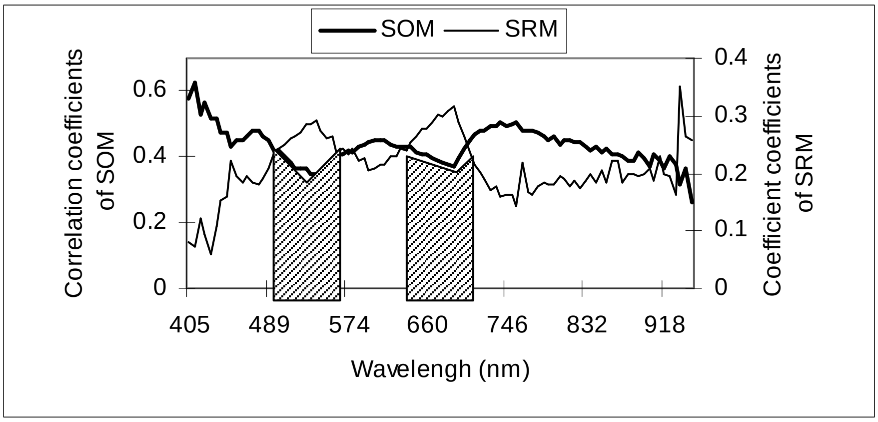

Figure 6: Correlogramme of the linear correlation between CASI-2 reflectance and SRM SOM on the Attert sites.

CONCLUSION AND PERSPECTIVE

The results of the present investigation demonstrate that SOM can be derived from hyperspectral remote sensing. It confirms previous studies in the southern Belgium. It is important to emphasize that the predictive equations are not universal, which requires that new field samples be collected and new regression equations constructed for every campaign. Indeed soil surface reflectance depends on many other factors than the soil organic matter that should all be taken into account to define an accurate relationship between SOM and the surface hyperspectral signal. However, the approach used in this paper already has the advantage of using small number of samples to establish the relationship between SOM and reflectance for a region, which can save time and cost in environmental studies.

Although this study has revealed the usefulness of the applied method for investigating the potential of reflectance spectra for SOM investigation, it should be noticed that disturbing factors effect remain an important problem. Their impacts are under study and an original end member spectrum unmixing model will be used to separate these disruptive elements of the SOM-soil reflectance relationship.

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