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Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study

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ABSTRACT

This paper compares predictions of soil organic carbon (SOC) using visible and near infrared reflectance (vis–NIR) hyperspectral proximal and remote sensing data. Soil samples were collected in the Narrabri region, dominated by Vertisols, in north western New South Wales (NSW), Australia. Vis–NIR spectra were collected over this region proximally with an AgriSpec portable spectrometer (350–2500 nm) and remotely from the Hyperion hyperspectral sensor onboard satellite (400–2500 nm). SOC contents were predicted by partial least-squares regression (PLSR) using both the proximal and remote sensing spectra. The spectral resolution of the proximal and remote sensing data did not affect prediction accuracy. However, predictions of SOC using the Hyperion spectra were less accurate than those of the Agrispec data resampled to similar resolution as the Hyperion spectra. Finally, the SOC map predicted using Hyperion data shows similarity with field observations. There is potential for the use of hyperspectral remote sensing for predictions of soil organic carbon. The use of these techniques will facilitate the implementation of digital soil mapping.

1. Introduction

Research in environmental monitoring, modelling and precision agriculture need good quality and inexpensive soil data. Hence we need the development of more time- and cost-efficient methodologies for soil analysis. Visible and near infrared reflectance (vis–NIR) spectroscopy is a physical non-destructive, rapid, reproducible method that provides inexpensive prediction of soil physical, chemical and biological properties according to their reflectance in the wavelength range from 400 to 2500 nm (Ben-Dor and Banin, 1995; Reeves et al., 2000, 2002; Dunn et al., 2002; Shepherd and Walsh, 2002; Islam et al., 2003). Reflectance signals are produced by vibrations in bonds between C, N, H, O, P, and S atoms. Weak overtones and combinations of fundamental vibrations due to the stretching and bending of NH, OH and CH groups dominate the NIR (700–2500 nm) and electronic transitions the visible (400–700 nm) portions of the electromagnetic (EM) spectrum (Ben-Dor et al., 1999). Soil organic carbon (SOC) plays a major role with respect to many chemical and physical processes in the soil environment and significantly affects the shape and nature of a soil reflectance spectrum. The wide spectral range found by different workers to assess SOC content suggests that SOC is an important soil constituent across the entire spectrum (Ben-Dor et al., 1999).

Spectroscopy has demonstrated its capability to accurately determine SOC contents in the laboratory (e.g. Reeves et al., 1999; Chang and Laird, 2002) and directly in the field with a portable spectrometer (e.g. Barnes et al., 2003). Imaging spectrometry can also be used to estimate soil properties. But the conditions of the soil surface can affect the spectral signal. Some of the properties that are subject to variation both in time and in space are: the degree of soil crusting as a result of rain-drop impact, soil texture, soil moisture, roughness and vegetation or crop residue cover. These perturbing factors induce changes in soil reflectance that approach or exceed the spectral response of organic matter (Barnes et al., 2003). In addition the soil properties estimation can also be subject to degradations due to radiometric and atmospheric effects, spectral and spatial resolutions (Lagacherie et al., 2008). Therefore because of these disturbing factors, few studies have demonstrated the capability to accurately determine SOC contents from airborne-hyperspectral sensors (e.g. Ben-Dor et al., 2002; Selige et al., 2006; Stevens et al., 2006) and none from satellite hyperspectral sensors. As remotely-sensed hyperspectral satellite data offer a synoptic view and a repetitive coverage which are two important advantages compared to ground observations and hyperspectral airborne data, the study of the potential of hyperspectral satellite data for SOC prediction becomes a major issue for digital soil mapping development.

Quantitative spectral analysis of soil using vis–NIR reflectance spectroscopy requires sophisticated statistical techniques to discern the response of soil attributes from spectral characteristics. Various methods have been used to relate soil spectra to soil attributes. Partial

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least-squares regression (PLSR) is one of the most common techniques for spectral calibration and prediction (e.g. McCarty et al., 2002; Chang and Laird, 2002). Viscarra Rossel et al. (2006) provide a review of the literature comparing quantitative predictions of various soil attributes using multivariate statistical techniques and spectral response in the visible, NIR and Mid infrared (MIR, 2500–25000 nm) regions of the electromagnetic spectrum. Among others, Viscarra Rossel et al. (2006) resume the literature comparing quantitative predictions of SOC using PLSR and spectral response in the visible, NIR and MIR regions of the electromagnetic spectrum.

The aims of this paper are to (i) evaluate the potential for measuring SOC using the Hyperion hyperspectral satellite remote sensor (400–2500 nm) and (ii) compare these to predictions of SOC made using field-collected vis–NIR spectra. In both instances partial least-squares regression (PLSR) was used to relate spectral measurements to SOC contents. This study was performed in the environs of Narrabri in north western New South Wales (NSW), Australia.

2. Materials and methods

2.1. Soil samples

A total of 146 surface soil samples (0–10 cm) was collected in the Narrabri region in north western NSW, Australia (−32°12'27"S, 149°36'31"E). This region is dominated by Vertisols. Eighty eight samples were collected in north western of Narrabri (−30°11'45"S, 149°37'18"E) in October 2006 and fifty eight soil samples near the town of Narrabri (−30°18'27"S, 149°45'4"E) in December 2006. Among the 88 soil samples collected in October 2006, 72 were collected on dry bare soils over cotton crops. For each studied cotton crop, a vis–NIR reflectance spectrum and soil sample at depth 0–10 cm were collected at the centre of a 20×20 m area, and four additional replicates were performed at the corners of the perimeter (Fig. 1a and c). And among the 88 soil samples collected in October 2006, 16 were collected on a travelling stock route along a transect (Fig. 1a and b). A travelling stock route is an uncultivated corridor of varying width from 100 to 500 m and scores to hundreds of kilometres in length used for the movement and grazing of cattle. As such in cultivated areas they represent useful areas for comparison with cultivated soil. In December 2006, soil samples were collected on pastures. In each instance, both vis–NIR reflectance spectra and soil samples at depth 0–10 cm were collected.

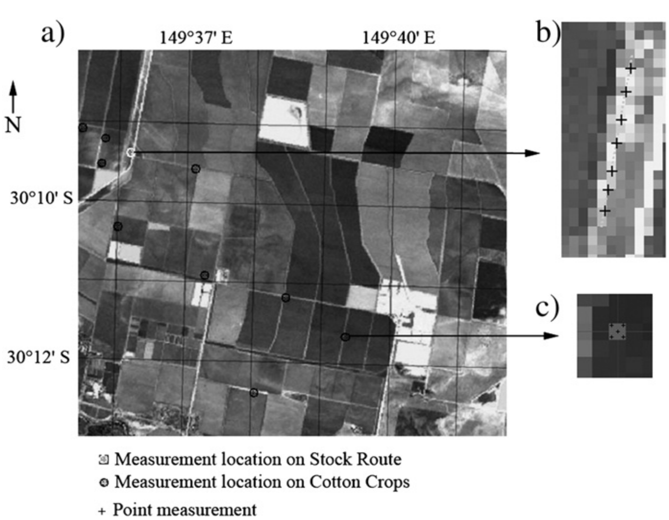

Fig. 1. a) Location of the measurements on cotton crops and the stock route, on a Hyperion image. b) Measurements over the stock route follow a transect. c) Over each cotton crop, four replicates were performed around the centre of the measurement, with a radius of 20 m.

The SOC content of these soil samples were measured by mid infrared (MIR) spectroscopy. For the MIR analysis, samples were ground to 200 µm for analyses as neat powders. The MIR spectral reflectance of each soil sample was measured using a Tensor 37_Fourier Transform Infrared spectrometer from Bruker Optics (Massachusetts, USA). Spectra were recorded from 2500 to 25 000 nm (4000–400 cm^{-1}) with 8 cm^{-1} resolution and 64 scans per second. Predictions of SOC content of each soil sample were made by using the partial least-squares regression (PLSR) from MIR calibrations for northern NSW derived by Viscarra Rossel et al. (2008). The calibration used 13 factors and the test set validation root mean squared error (RMSE) of the model was 0.15 dag/kg and $R^2_{adj.}$ of 0.91. Further details on the methodology and calibration can be found in Viscarra Rossel et al. (2008).

2.2. Field vis–NIR measurements

The reflectance of the 146 soil samples was measured on the field with the AgriSpec portable spectrometer (Analytical Spectral Devices, Boulder, Colorado). The AgriSpec spectrometer has a light source and measurements are made using the contact probe (Analytical Spectral Devices, Bolder, Colorado). It offers a full spectral range (350–2500 nm) and rapid data collection (10 scans per second). A white spectralon panel (5×5 cm) provided the absolute reflectance factor for field measurements. The surface scanned was a core of 10 cm and 10 scans were made per sample. The spectralon panel was systematically measured before each sample measurement, using 50 replicates. A spectrum recorded by the AgriSpec instrument and corresponding to a soil sample of travelling stock route with 4.49% SOC is represented on Fig. 2.

2.3. Hyperion hyperspectral data

Two Hyperion hyperspectral data were acquired over the Namoi Valley in Australia (−32°12'27"S, 149°36'31"E). The first one was acquired on the 13 December 2006 at 23:51 UT over pasture soils (Fig. 3a and c) and the second one was acquired on the 17 January 2007 at 23:47 UT over cropping soils and travelling stock routes (Fig. 3a and b).

The Hyperion sensor on board the EO-1 satellite measures the radiance from 400 to 2500 nm, with 242 spectral bands with approximately 10 nm of spectral resolution and 30 m of spatial resolution. The swath width of the Hyperion images is 7.6 km (Fig. 3a). However, in spite of radiometric and geometric corrections, the Signal to Noise Ratio (SNR) is low (~50:1). A detailed description of Hyperion characteristics, operations and applications can be found in Folkman et al. (2001). To derive surface reflectance from the radiance data, the radiance data must be corrected for solar irradiance and atmospheric effects such as two-way transmission, multiple scattering, and path radiance. Several methods can be used, involving either the need for in situ spectral reflectance measurements on the ground, and/or the use of radiative transfer atmospheric correction algorithms. Here a radiative transfer algorithm was used to derive reflectance from Hyperion radiance, without prior knowledge. This algorithm is 'The Atmospheric Removal Program' (ATREM) developed by Gao and Goetz (1990) and Gao et al. (1993) and using an approximate radiative transfer code called 'Simulation of the Satellite Signal in the Solar Spectrum (5 S)' (Tanre et al., 1986). Finally, the channels with a very low SNR and those located in the atmospheric absorption bands are removed. Thus work was carried out using 152 Hyperion bands.

One aim of this paper is to compare SOC predictions made using the Hyperion hyperspectral satellite remote sensor (400–2500 nm) to SOC predictions made using field-collected vis–NIR spectra. To perform this comparison, the field spectra recorded by the AgriSpec instrument were resampled to cover the spectral range of Hyperion data with the same spectral resolution as Hyperion data. These resampled spectra have 152 spectral bands from 427 to 2355 nm. The spectrum recorded by the AgriSpec instrument and corresponding to a

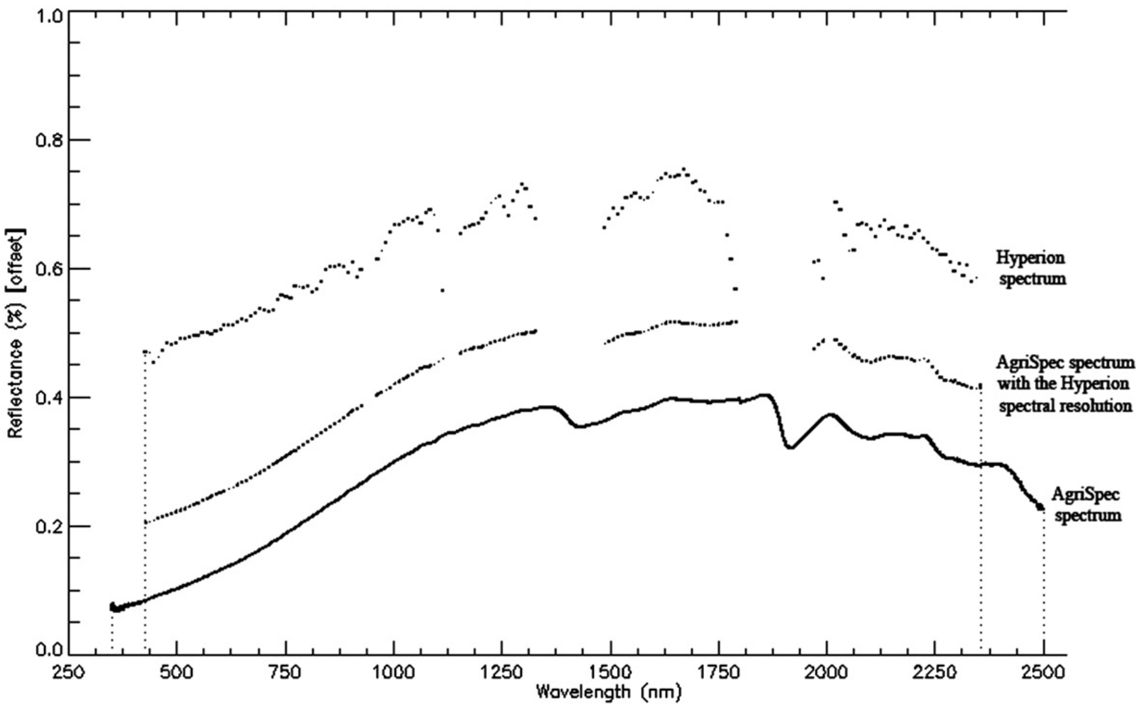

Fig. 2. Plot of an AgriSpec high resolution spectrum (2151 spectral bands) of a soil sample on travelling stock route, an Agrispec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands) of the same soil sample, and the Hyperion spectrum of the stock route.

soil sample of travelling stock route which has a SOC content of 4.49% was resampled to cover the spectral range of Hyperion data and plotted on Fig. 2. Moreover the Hyperion spectrum corresponding to the same travelling stock route is also represented on Fig. 2. On Fig. 2 the Hyperion spectrum which contains noise, can be compared to the AgriSpec spectrum resampled to the Hyperion spectral resolution.

2.4. Predictions of soil organic carbon

Partial least-squares regression (PLSR) with leave one-out cross-validation was used for SOC predictions using both the field spectra and the Hyperion remotely-sensed satellite data. The root mean squared error (RMSE), coefficient of determination (R^2) and ratio of performance to deviation (RPD) were used to evaluate the performance of SOC prediction models. We used the ParLeS software (Viscarra Rossel, 2008) for the spectroscopic and chemometric analysis. The RPD was computed in order to interpret the prediction ability of each model (Chang and Laird, 2002). RPD is the ratio between the standard deviation of the reference method against that of the RMSE. Chang and Laird (2002) defined three classes of RPD: category A (RPD$>$2) are models that can accurately predict the property in question, category B (RPD between 1.4 and 2) is an intermediate class which regroups models that can be possibly improved, and models falling in category C (RPD$<$1.4) have no prediction ability.

2.5. Soil sample sets used to compare vis–NIR field and Hyperion data

The first aim of this paper is to compare predictions of SOC made (i) using spectra with the Hyperion spectral resolution (152 spectral bands) and (ii) using spectra collected on the field with the AgriSpec instrument (2151 spectral bands). To perform this analysis, four soil sample sets were studied. Each soil sample set has a specific distribution, number of data and SOC content range. The characteristics of the soil sample sets are presented in Table 1.

The first soil sample set called "Cropping soils" contains all the soil samples (72) collected on the North–West of Narrabri in October 2006 over cotton crops. All the soil samples of this set have a SOC content between 0.54 and 1% and the SOC contents showed a skewed distribution (Table 1). The second soil sample set called "Pasture soils" contains soil samples collected over pasturages and stock routes which have a SOC content superior to 1%. Fifty eight soil samples were collected over pasturages and 16 over stock routes, but among these soil samples, 18 have a SOC content inferior to 1%. Thus the second soil sample set called "Pasture soils" contains 56 soil samples. These soil samples have a SOC content between 1.08 and 5.1% and these SOC contents showed a skewed distribution (Table 1). The third soil sample set included all the soil samples collected on the field (146) and was called "Total soil database". The soil samples have a SOC content between 0.002 and 5.1% and these SOC contents showed a Poisson distribution with 60.9% of the SOC values ranged from 0 to 1% (Table 1). The fourth soil sample set called "Soils over Hyperion images" consisted of 72 soil samples. This fourth soil sample set contained the mean of the 5 soil samples measurements for each cotton crop (Fig. 1c), added to the pasture and stock routes soil samples that are located in the Hyperion images. The SOC content of the "Soils over Hyperion images" showed a Poisson distribution with 37.5% of the SOC values ranged from 0 to 1% (Table 1).

2.6. Soil sample set used to evaluate the potential of Hyperion data

The second aim of this paper is to evaluate the potential of SOC prediction using the reflectance data recorded by the Hyperion hyperspectral sensor. This work investigates the SOC mapping from Hyperion hyperspectral data using the PLSR method.

First, partial least-squares regression was used to make the prediction model necessary to estimate the SOC contents from Hyperion hyperspectral data. The soil sample set used to make this prediction model consisted of 52 soil samples spectra, and was called "Soils over Hyperion test area". All the 52 soil samples are located on a small area of the Hyperion image acquired on the 13 December 2006 at 23:51 UT over pasture soils (Fig. 3c). The surface of this area is around 5.8×2.8 km. The SOC contents of the "Soils over Hyperion test area" showed a skewed distribution. The soil samples have a SOC content between 0.002 and 5.1%, from the results obtained by MIR analysis. The SOC mean, variance and standard deviation of this soil samples set

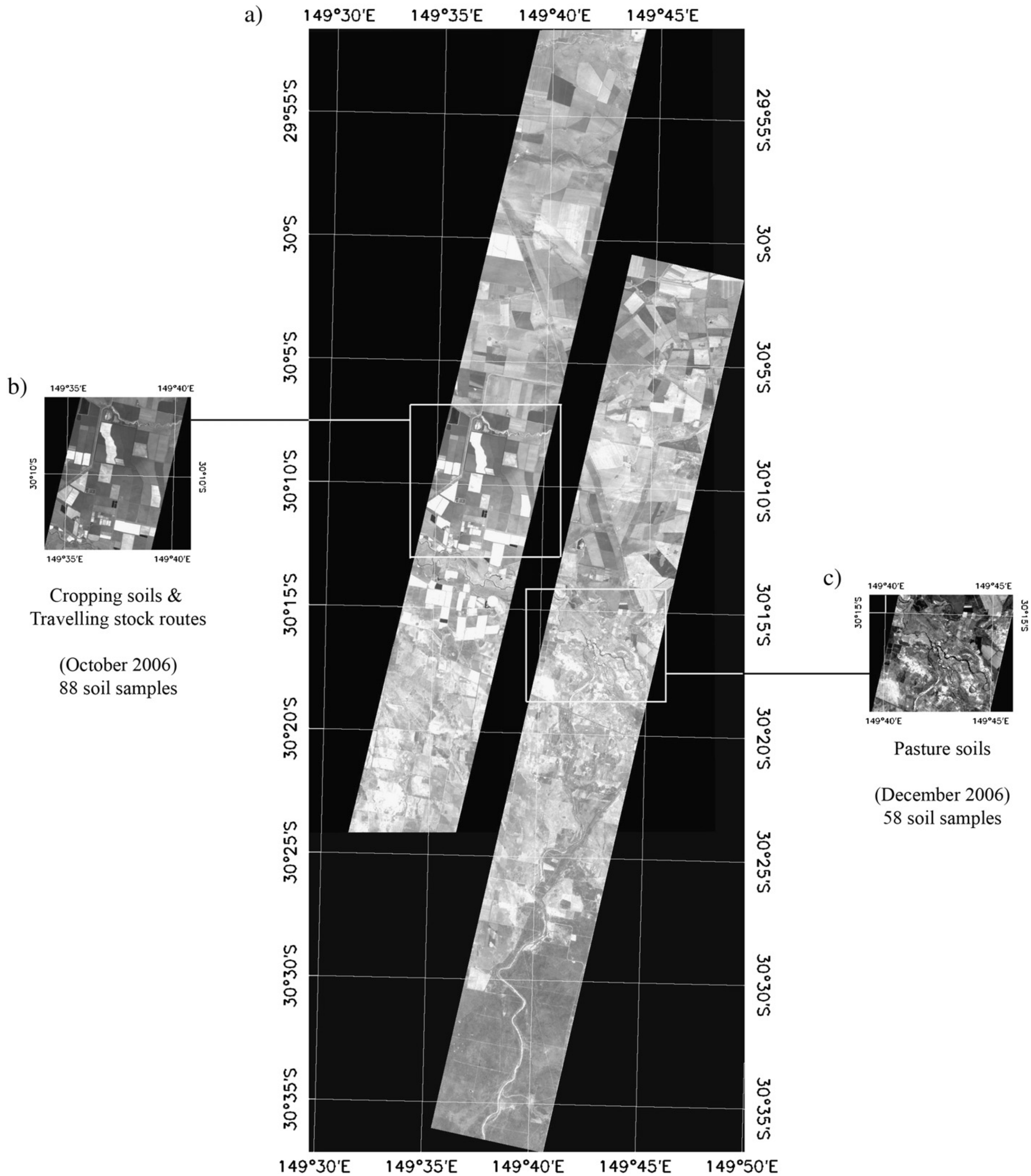

Fig. 3. a) Hyperion Images on Namoi Valley, b) studied area during the field trip in October 2006, and c) studied area during the field trip in December 2006.

are respectively 1.7, 1.67 and 1.11. The reflectance spectra used to construct this prediction model are the Hyperion spectra associated with the 52 soil samples. Then, a cross-prediction step was performed from the Hyperion spectra of each pixel of a test area. The test area corresponds to a part of the Pastures zone studied during the field trip in December 2006. The region was selected because of the SOC heterogeneity and the soil composition diversity (crops, pastures, bare dry soils, fluvial network).

3. Results of SOC prediction with AgriSpec spectra

3.1. Predictions for soils containing low amounts of SOC

The "Cropping soils" were used to determine if low SOC contents can be estimated by the spectral resolutions of the AgriSpec and Hyperion hyperspectral instruments. Baumgardner et al. (1970) noted that if the SOC drops below 2%, it has only a minimal effect on spectral

Table 1
Characteristics of the soil sample sets: minimum, maximum, mean, variance and standard deviation for the four soil sample sets

Soil sample set	Description of field	Samples number	Minimum SOC content	Maximum SOC content	Mean SOC content	Median	Standard Deviation
"Cropping soils"	Cotton crops	72	0.54	1.00	0.70	0.69	0.1
"Pasture soils"	Pasture and stock routes	56	1.08	5.10	2.31	2.06	0.89
"Total soil database"	Pasture, stock routes and cotton crops	146	0.002	5.10	1.28	0.8	0.95
"Soils over Hyperion images"	Pasture, stock routes and cotton crops located on Hyperion images	72	0.002	5.10	1.59	1.47	1.03

response. As the maximum value of the SOC for this "Cropping soils" is 1%, the spectral response of the studied soil samples should be affected poorly by the SOC content. The cross validations for SOC content for the "Cropping soils" provide a RPD of 1.03 and 0.98 respectively using the AgriSpec high resolution spectra (2151 spectral bands) and the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands). Fig. 4 presents measured vs. predicted values of SOC content for the two types of spectra. So from the RPD no SOC cross validation model using our "Cropping soils" has prediction ability, whatever the spectral resolution.

3.2. Predictions for soils containing higher amounts of SOC

The "Pasture soils" were used to determine if medium and high SOC contents can be estimated by the spectral resolutions of the AgriSpec and Hyperion hyperspectral instruments. The cross validations for SOC content for the "Pasture soils" provide a RPD of 1.32 and 1.33 respectively using the AgriSpec high resolution spectra (2151 spectral bands) and the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands) (Fig. 5). From the RPD, the spectral resolution did not change the results of the models. Cross validations are better with SOC contents over 1% than with SOC contents under 1% (Figs. 4 and 5). But although the cross validations are better with SOC contents between 1.08 to 5.1%, the predictions are nevertheless mediocre.

3.3. SOC predictions for soils containing a wide range of SOC

All 146 samples, contained in the "Total soil database", were used to derive the PLSR calibrations using both the spectral resolutions of AgriSpec and Hyperion hyperspectral instruments. The cross validations for SOC content for the "Total soil database" provided a RPD of 1.87 and 1.92 respectively using the AgriSpec high resolution spectra (2151 spectral bands) and the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands). Fig. 6 presents measured vs. predicted values of SOC for the 2 types of spectra. The prediction R^2, RMSE and RPD obtained with the "Total soil database" are better than with the "Pasture soils" and the "Cropping soils". For soils with SOC contents between 0.002 and 5.1%, both AgriSpec and Hyperion spectral resolutions provided excellent cross validation. And the spectral resolution did not change the accuracy of the models.

4. Results of SOC prediction with Hyperion spectra

From Section 3, both AgriSpec and Hyperion spectral resolutions provided excellent cross validation when the soil sample set is more comprehensive. Using the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands) were as useful as the high-spectral resolution of the AgriSpec instrument.

The "Soils over Hyperion images" were used to determine if SOC contents can be estimated by Hyperion hyperspectral data. The cross validations for SOC content for the "Soils over Hyperion images"

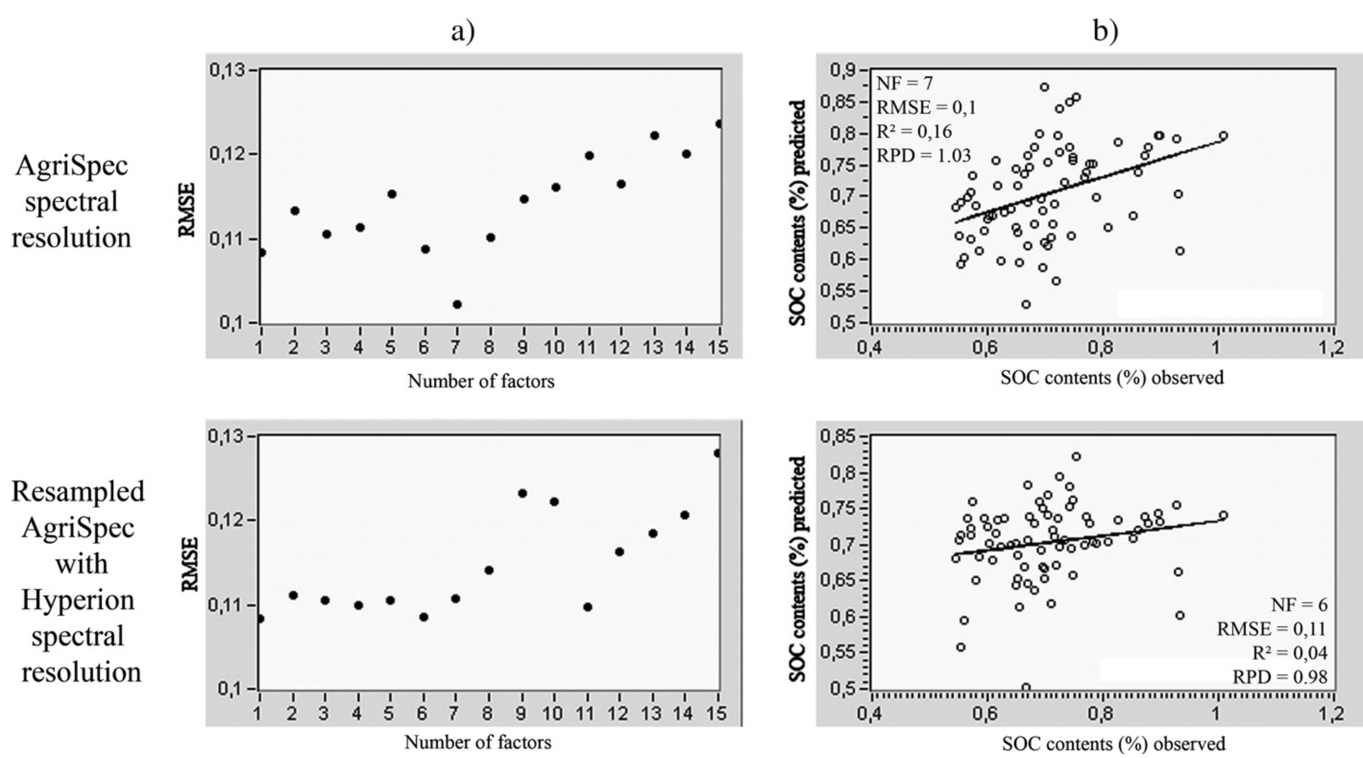

Fig. 4. Column: a) shows the cross validated root mean square error (RMSE) of prediction against the number of factors (NF); b) shows the observed against the cross validated PLSR predictions of SOC content (%) for the "Cropping soils".

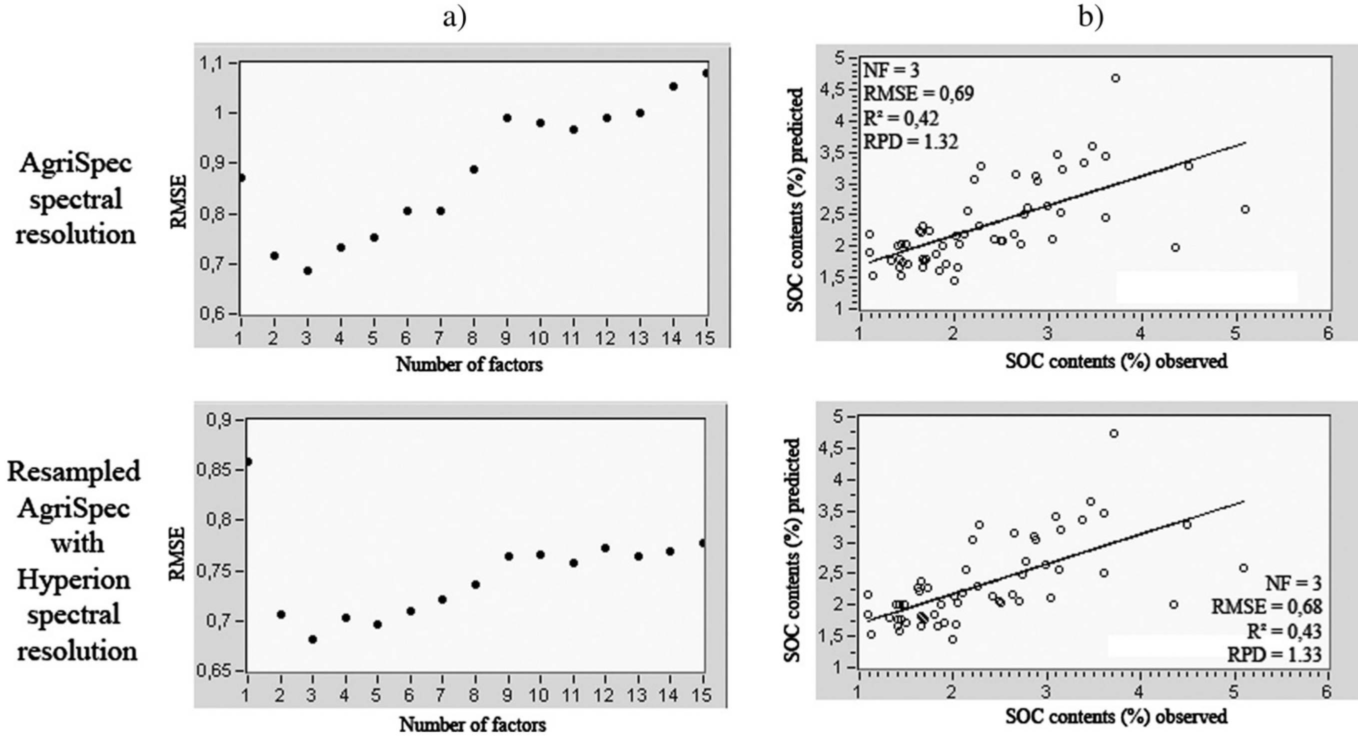

Fig. 5. Column: a) shows the cross validated root mean square error (RMSE) of prediction against the number of factors (NF); b) shows the observed against the cross validated PLSR predictions of SOC content (%) for the "Pasture soils".

provided a RPD of 1.69, 1.75 and 1.43 respectively using the AgriSpec high resolution spectra (2151 spectral bands), the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands) and the Hyperion hyperspectral data. Fig. 7 presents measured vs. predicted values of SOC for the 3 types of spectra. Both AgriSpec high resolution spectra (2151 spectral bands) and AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data (152 spectral bands) provided good predictions of SOC for the 72 "Soils over Hyperion images". So the spectral resolution did not change the accuracy of the model. But the SOC prediction model using Hyperion hyperspectral spectra is less accurate than that of the AgriSpec spectra resampled to the low

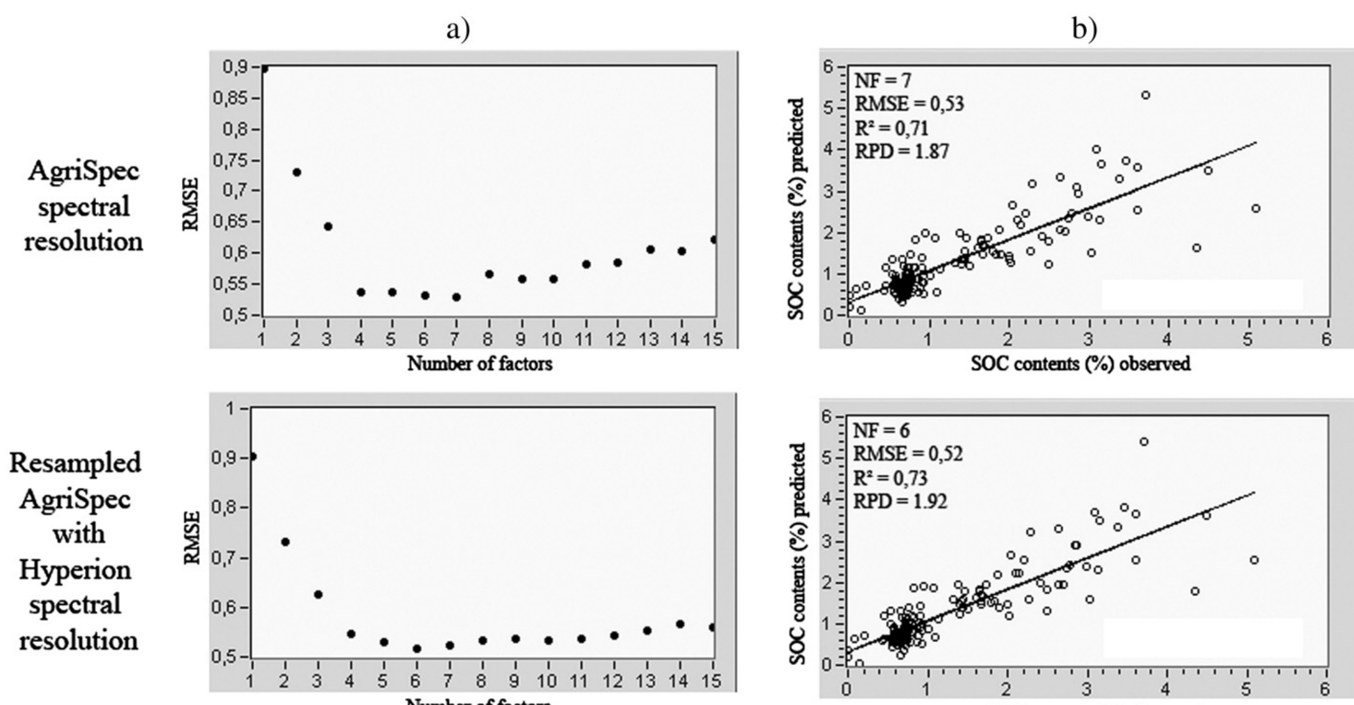

Fig. 6. Column: a) shows the cross validated root mean square error (RMSE) of prediction against the number of factors (NF); b) shows the observed against the cross validated PLSR predictions of SOC content (%) for the "Total soil database".

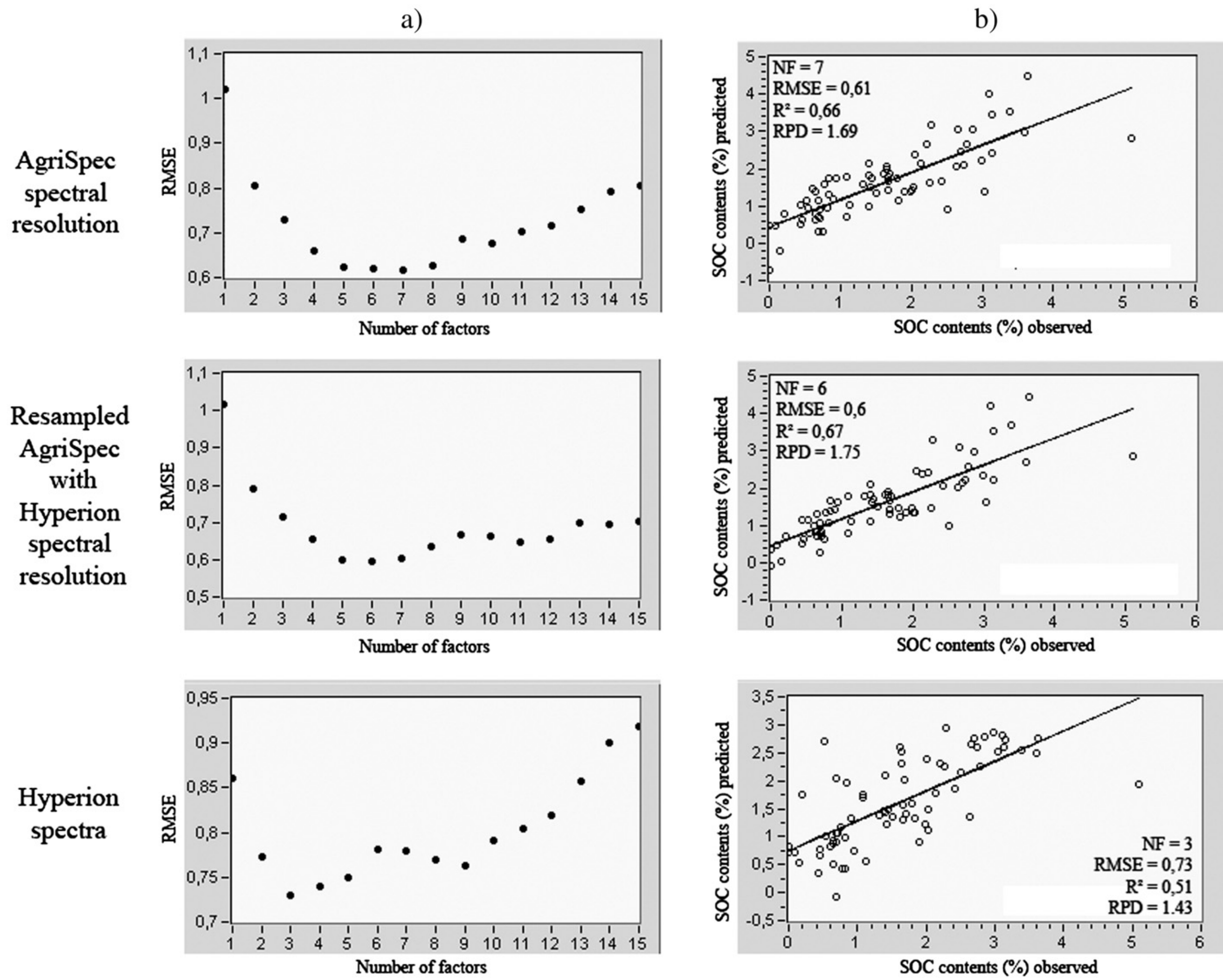

Fig. 7. Column: a) shows the cross validated root mean square error (RMSE) of prediction against the number of factors (NF); b) shows the observed against the cross validated PLSR predictions of SOC content (%) for the "Soils over Hyperion images".

spectral resolution similar to that of the Hyperion data. The SOC prediction model using Hyperion hyperspectral spectra has a RPD of 1.43 which indicates a very low accuracy of prediction.

The results obtained from the four soil samples sets (Figs. 4–7) lead to suggest the SOC prediction models seems to be sensitive to the number of soil samples. Using the AgriSpec spectral resolution, the prediction model built in using the "Total soil database" (146 soil samples collected over the Vertisols of the Narrabri area, with SOC content between 0.002 and 5.1%) is more accurate than the prediction model built in using the "Soils over Hyperion images" (72 soil samples collected over the Vertisols of the Narrabri area, with SOC content between 0.002 and 5.1%). And using the AgriSpec spectral resolution, the prediction model built in using the "Soils over Hyperion images" (72 soil samples collected over the Vertisols of the Narrabri area, with SOC content between 0.002 and 5.1%) is more accurate than the prediction model built in using the "Pasture soils" (56 soil samples collected over the Vertisols of the Narrabri area, with SOC content between 1.08 and 5.1%).

5. SOC mapping from Hyperion data

When the amount of SOC dropped below 1%, reflectance spectra are not able to predict SOC contents, whatever the spectral resolution. As we observed on the field that bare cotton crops had very low SOC contents, we cannot perform SOC prediction from Hyperion data on an area covered by cotton crops. So the SOC prediction from Hyperion data was performed over mainly pastures, as described in the Section 2.6, which contains a wide SOC contents range. The cross-validation step was performed with the "Soils over Hyperion test area" which contain 52 soil samples located on the Hyperion image acquired in December 2006 (Fig. 3a and c). The cross validation for SOC content provided a RPD of 1.42, a prediction R^2 of 0.493 and a RMSE of 0.8%. Then, the cross-prediction step was performed from the Hyperion spectra of each pixel of the studied area. In spite of the low RPD, the SOC prediction result (Fig. 8a) shows similarities with the field observations. As the SOC prediction result is not correlated with the Normalized Difference Vegetation Index (NDVI) (Fig. 8a and b), the SOC predictions are not influenced by the vegetation cover. First, the fluvial network is mapped with no SOC which is correct. Secondly, a bare crop located on the North–East part of the area, has a low SOC contents predicted. This result is coherent with the field observations done during the field trip in October 2006: all the bare crops observed had a low SOC (under 1%). Third, the pastures located on the West part of this studied area, have a high predicted SOC contents (over 2%). This result is coherent with the field observations done during the field trip in December 2006: all the pastures observed had a high SOC content

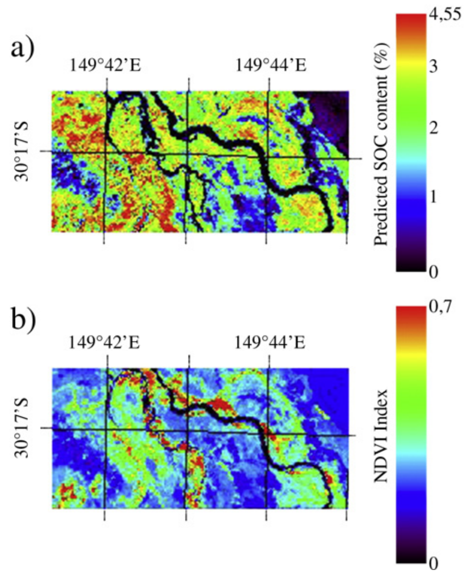

Fig. 8. a) Spatial distribution of the predicted SOC content and b) Normalized Difference Vegetation Index (NDVI) map.

(under 2%). Finally, the bare dry soils located on the West part of this studied area, have a low SOC contents predicted (under 1.5%). During the field trip in December 2006, we have observed no vegetation of organic matter on the surface of these dry bare soils.

6. Discussion

This paper shows that whatever the SOC ranges of the soil samples (between 0.54 and 1%, between 1.08 and 5.1%, or between 0.54 and 5.1%) and whatever the number of soil samples (56, 72 or 146) used in the prediction models, the spectral resolution did not change the accuracy of the model. So in our agricultural and pedological context of the Narrabri area, the use of Hyperion hyperspectral data should be as useful as the use of field vis–NIR data for SOC prediction. However, we observed the SOC prediction model using Hyperion hyperspectral data was less accurate than that of the AgriSpec spectra resampled to the low spectral resolution similar to that of the Hyperion data. This drop in accuracy may be due to two factors: the noise present in the Hyperion spectra and the Hyperion spatial resolution of 30 m. The noise degrades the signal and may hide spectral features of SOC in the spectra. Hidden, these spectral features of SOC cannot be used by the PLSR to predict the SOC content. The spatial resolution of 30 m can lead to study mixed surface (soil mixed with vegetation, road, rocks…). So the remotely spectra corresponding to these mixed surfaces contain a mixture of information about the surface components. The mixture of information in the spectra may lead to hide spectral features of SOC.

Moreover from the results of this paper we can assume that a high variability of SOC contents in the soil data set and a high number of soil data could be a factor of improvement of the SOC prediction accuracy. Indeed the best prediction model is built from 146 soil data which have a SOC range from 0.002 to 5.1%. So, a large collection of soil samples on the field seems to be needed to build an accuracy prediction model.

An Environmental Mapping and Analysis Program (EnMAP) satellite will be launched in 2010, with have onboard a hyperspectral sensor which will provide high-spectral resolution observations over the wavelength range from 420 to 2450 nm (Stuffler et al., 2007). The spatial ground sampling distance will be 30 m and the Signal to Noise Ratio of EnMap should be better than that of Hyperion. As we show that the Hyperion spectral range can be used to predict SOC content using PLSR, future research may be directed to the use of such hyperspectral data to predict SOC content more accurately.

To fulfill the increasing demand on accurate, quantitative information on the evolution of terrestrial ecosystems, research is required to develop satellite hyperspectral techniques. Recent approaches to make digital soil maps based on geographical information systems indicate that soils can be predicted from other soils attributes at the same location or from soil and environmental attributes from neighboring locations (McBratney et al., 2003). Remote sensing data, especially for areas where the soil surface is permanently or temporarily exposed may be an important tool for acquiring geographical information about soils. As we show that SOC prediction results obtained from Hyperion data show similarities with the field observations, SOC maps obtained using remote sensing satellite data is encouraging. Hyperspectral remote sensing approach is promising for SOC mapping and may reinforce the development of digital soil mapping methods.

7. Conclusions

We used for the first time satellite hyperspectral data for SOC prediction by multivariate regression modelling. This remote sensing satellite approach shows the theoretical potential of satellite hyperspectral data for SOC prediction. The results indicate that whatever the SOC ranges of the soil samples and whatever the number of soil samples used in our prediction models, the spectral resolution did not change the accuracy of the model. The cross validation models using 146 soil samples with a SOC range from 0.002 to 5.1% have a RPD of 1.87 and 1.92 respectively using the high resolution AgriSpec data and the AgriSpec spectra resampled to match the resolution of the Hyperion data. But the cross validation models using Hyperion hyperspectral data were inaccurate. The cross validation model using 72 soil samples with a SOC range from 0.002 to 5.1% has a RPD of 1.43 using Hyperion hyperspectral data. Considering these results we can assume that this drop in accuracy may be due to two factors: the noise present in the Hyperion spectra and the Hyperion spatial resolution of 30 m. The results presented in this paper lead us to the suggestion to increase the studies in spectral unmixing, needed to extract the soil spectra from the mixed hyperspectral data when the spatial resolution is 30 m. And it is suggested that researches in SOC prediction from satellite hyperspectral data may be followed through from the German hyperspectral satellite (EnMAP) data which may have a better Signal to Noise Ratio.

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