Performance of spectrometers to estimate soil properties

M. T. Eitelwein[1], J. A. M. Demattê[2], R. G. Trevisan[1], A. A. Anselmi[1], J. P. Molin[1]
[1]Biosystems Engineering Department, ESALQ-USP, Piracicaba-SP, Brazil
mateus_eitelwein@usp.br
[2] Soil Science Department, ESALQ-USP, Piracicaba – SP, Brazil

Abstract

The objective of this work was to compare soil spectral reflectance readings obtained by two spectrometers and evaluate their potential to predict soil attributes. A total of 261 samples were used which were collected in the depth ranges 0-0.2, 0.4-0.6 and 0.8-1 m. The samples were sent to a laboratory to determine soil granulometry (particle size distribution); soil organic matter (SOM) and chemical elements (K, Ca, Mg and H + Al) to calculate CEC. Two instruments were used for the spectral readings. The comparison of sensor readings from both spectrometers using Pearson linear correlation was good in the range 400 – 1900 nm. The predictions of soil attributes using partial least squares regression (PLSR) exhibited significant possibilities for determining soil physicals characterists, such as sand and clay. This is an ongoing study and a third instrument will be used for new comparisons.

Keywords: chemometrics, Vis-NIR spectroscopy, proximal soil sensig.

Introduction

Nowadays, determination of soil properties using techniques based on the electromagnetic spectrum give good results when the visible (Vis; 400-700nm), near infrared (NIR; 700-2500nm) and middle infrared or thermal (MIR or TIR; 2500 – 25000 nm) (Viscarra Rossel et al., 2006; Chabrillat et al., 2013) are used. The advantages of the technique are that it is low-cost, non-destructive, residue free and providing real-time soil observation (Maleki et al., 2008; Mouazen et al, 2005; Kodaira & Shibusawa, 2013).
Some authors state that, in certain cases, the spectroscopy of reflectance linked with techniques of multivariate statistics can be more precise than the methods traditionally used to determine some soil attributes (McCarty et al., 2002; Lugassi et al., 2014).
In Brazil, the study of these chemometric techniques applied to precision agriculture are practically inexistent. On the other hand, we have a good amount of work using reflectance spectroscopy (Vis-NIR) to assist pedologists in soil classification, which is currently being built a Brazilian soil spectral library (Demattê & Land, 2014; Araújo et al ., 2014). Some models of more robust spectrometers are being commercialized with the aim of direct application in the field. Nevertheless, the spectral relations still have to be well understood by first using this equipment under controlled conditions.
The objective of this work was to compare the spectral readings of two spectrometers and evaluate their potential to predict soil attributes.

Material and methods

Soil Samples

The soil samples used in laboratory belong to the Soil Spectral Library of Brazil (BESB). A total of 261 soil samples were utilized, collected along the soil profile in the depth ranges 0-0.2, 0.4-0.6 and 0.8-1m. After the soil extraction, the samples were dried at a temperature of 45°C for 24 h, cooled and passed therough a 2 mm sieve. Afterwards, the samples were sent to a laboratory where physical and chemical properties were analysed. The particle analysis was done in accordance with the procedures proposed by Embrapa (1997), where the fraction of clay of the soil is measured by densimetry, the sand content by sieving and the silt fraction composes of remaining part of the sample. The chemical analysis of K, Ca, Mg and H + Al was processed in a laboratory according to the methodology proposed by Raij et al. (2001) and the cation exchange capacity (CEC) at pH 7 was obtained from these results. The determination of the soil organic matter contents were done by wet oxidation with a solution of potash dichromate (0.167 mol L^{-1}) being indirectly estimated by titration of the chromium íons (Cr^{3+}) remaining after oxidation, with ammoniac iron sulphate (0.1 mol L^{-1}).

Spectral aquisition

The two instruments used for spectral data acquisition were: FieldSpec 3 (ASD, Boulder, Colorado, USA) with spectral range from 350 to 2500 nm (Vis-NIR) and spectral resolution of 3 to 10 nm; and AgroSpec (Tec5, Oberursel, Germany) with spectral range from 305 to 2205 nm (Vis-NIR) and spectral resolution from 10 to 16 nm.
The spectral readings were obtained in a dark environment to minimize diffuse radiation. Both readings were retrieved from soil samples placed in petri plates. For the FieldSpec 3, the optical fiber cable was positioned 0.08 m from the sample using, as illumination sources, two 50W halogen lamps, offset 0.35m from the sample supported at a zenith angle of 30 degrees. For the AgroSpec, the reading were taken by positioning the measuring head at 0.01 m from the sample; the latter instrument has an integrated energy source (light) within the optical fiber cable to both emit and simultaneously read energy. As a standard reference of reflectance, for obtaining radiometric data in reflectance values, a Spectralon plate was used, taking into account that this material provides nearly 100% reflectance. Calibration readings using the standard plate were made every 20 minutes for the acquisition of the spectral information.

Data analysis

Initially, the soil chemical and physical data were submitted to descriptive statistical analysis. A Pearson correlation was obtained between the spectral readings of both instruments and data presented graphically. No pre-treatment was used in the spectral data and the whole spectral ranges of the spectrometers were used to create the model. Models of prediction of the soil attributes were generated through partial least squares regression (PLSR) with cross validation (leave-one-out) using the software The Unscrambler X v. 10.3 (CAMO Software, Oslo, Norway).

Results

Descriptive statistics of soil attributes are shown in Table 1. There was a wide range of variation in parameters evaluated, mainly because of the variety of soil types and stratification of samples at different depths tested.

Table 1. Descriptive statistics of soil attributes analyzed in 261 soil samples.

Soil Attributes	Mean	Max	Min	Median	Std Dev.	Skewness	Kurtosis
Sand (g/kg)	538.77	936	20	614	312.17	-0.19	-1.64
Silt (g/kg)	78.06	303	1	42	80.21	1.44	0.89
Clay (g/kg)	383.19	847	40	331	265.53	0.30	-1.37
SOM[1] (g/kg)	15.88	47	2.4	14	9.98	0.88	0.06
CEC[2] (mmolc/dm^3)	33.07	110.3	5.3	25.3	23.91	1.28	0.96

[1]Soil organic matter; [2]Cation exchange capacity (pH 7).

The FieldSpec sensor, which has a higher resolution and spectral range, showed smoother curves as compared with the AgroSpec sensor, especially in regions below 420 nm and above 1850 nm, where the AgroSpec sensor showed larger amounts of noise and random values in sensor readings (Figure 1).

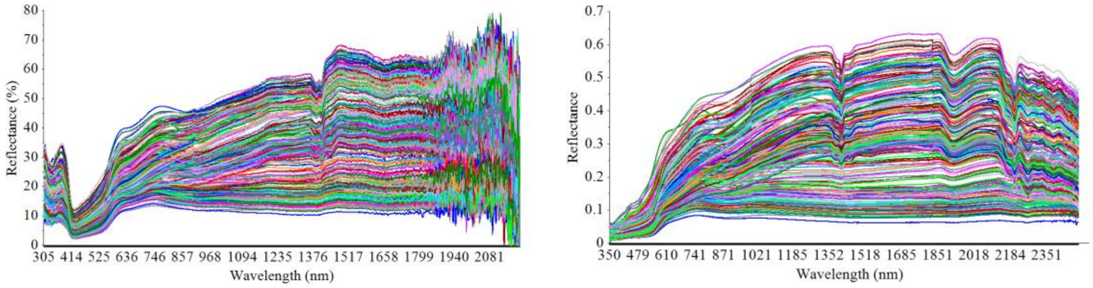

Figure 1. Spectral curves of reflectance from AgroSpec (left) and FieldSpec 3 (right) equipment.

The comparison between the acquisitions of the two instruments is shown in Figure 2. The correlation coefficients are high (above 0.95) and stable between 400 and 1900 nm. The high noise found in AgroSpec sensor data outside this range (Figure 1) contributed to reducing correlation coefficients in those regions of the spectrum.

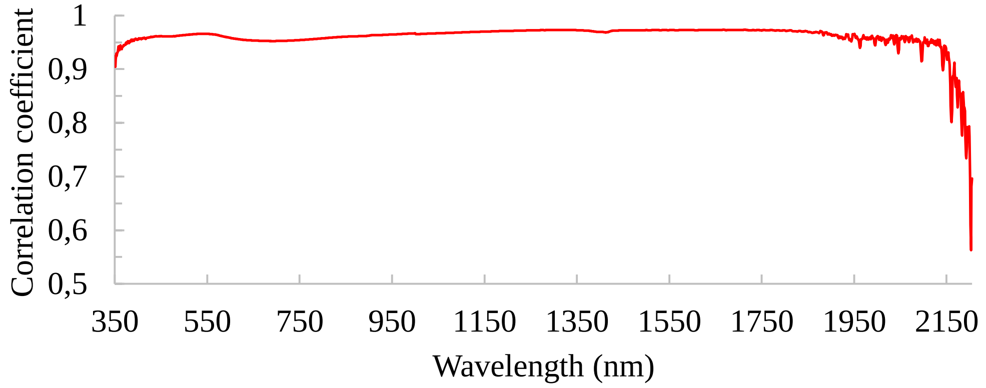

Figure 2. Correlation coefficients between spectral readings of AgroSpec (Tec5) and FieldSpec 3 (ASD Inc.) for 261 soil samples.

The predictions of soil attributes using the PLSR models are shown in Figure 3. Based on the greater r^2 and lower RMSE values, it can be observed that the FieldSpec 3 sensor gave better results in cross-validation for all attributes, with the best performance found for estimating the sand and clay contents of soil.

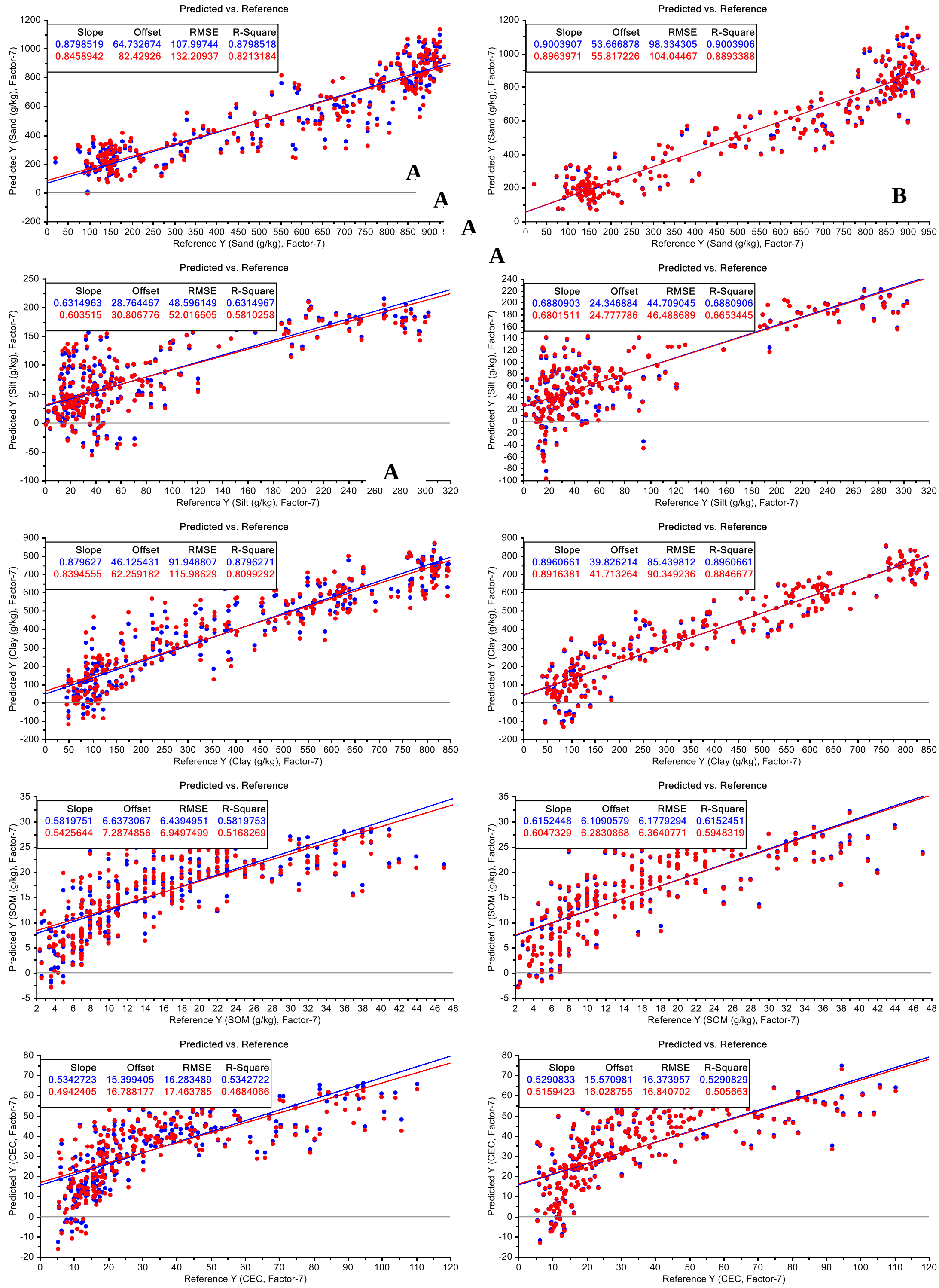

Figure 3. Results of predicted and reference values from the PLSR model using full cross validation. AgroSpec is shown on the left and FieldSpec on the right. Blue points indicate calibration model and red points validation.

Discussion

Both instruments displayed high correlation between readings within the range of 400 to 1900 nm. AgroSpec data contained some noise through all its sampling range leading to

lower correlations and reducing its estimation capabilities when compared to FieldSpec 3. The comparison between readings with a second instrument showed that the fluctuations of reflectance in this range do not relate to the properties found in the samples but to some other factor related to the hardware. Aiming to reduce this noise, it is recommended to decrease the initial and final range of reading of the AgroSpec. Kuang et al. (2015), operating the AgroSpec in the field also report noise in these spectral regions.
The models of prediction of soil attributes, predidicted the soil physical properties (sand and clay) better, probably because this aspect strongly affects the intensity of reflectance of the readings. The use of spectral data without transformation or treatment in PLS regressions showed promising results for some variables.

Conclusions

The spectral reflectance readings of the sensors evaluated showed a high correlation between bands in the range of 400 to 1900 nm. However, caution is advised when using AgroSpec sensor data outside this range.
The prediction of soil attributes using spectral reflectance (Vis-NIR) was most successful for the soil physical attributes, mainly sand and clay, indicating good potential for the use of this instrument to predict these variables. This is an ongoing study and a third instrument will be used for new comparisons.

Acknowledgements

The authors acknowledge with gratitude the São Paulo Research Foundation (FAPESP) for providing a doctoral scholarship to Mateus T. Eitelwein (Project number 2014/10737-3) and the company Jacto for loaning the sensor.

References

Araújo, S. R., Wetterlind, J., Demattê, J. A. M., Stenberg, B. 2014. Improving the prediction performance of a large tropical vis-NIR spectroscopic soil library from Brazil by clustering into smaller subsets or use of data mining calibration techniques. European Journal of Soil Science, 65 718-729.

Chabrillat, S., Ben-dor, E., Viscarra Rossel, R. A. V., Demattê, J. A. M. 2013. Quantitative Soil Spectroscopy (Editorial). Applied and Environmental Soil Science, 2013 1-3.

Demattê, J. A. M., Terra, F. S. 2014. Spectral pedology: A new perspective on evaluation of soils along pedogenetic alterations. Geoderma, 217-218 190-200.

Kodaira, M., Shibusawa, S. 2013. Using a mobile real-time soil visible-near infrared sensor for high resolution soil property mapping. Geoderma, 199 64-79.

Kuang, B, Tekin, Y., Mouazen, A. M. 2015. Comparison between artificial neural network and partial least squares for on-line visible and near infrared spectroscopy measurement of soil organic carbon, pH and clay content. Soil & Tillage Research, 146 243-252.

Maleki, M. R., Mouazen, A. M., De Ketelaere, B., Ramon, H., De Baerdemaeker, J. 2008. On-the-go variable-rate phosphorus fertilization based on a visible and near-infrared soil sensor. Biosystems Engineering, 99 35-46.

Mouazen, A. M., De Baerdemaeker, J., Ramon, H. 2005. Towards development of online soil moisture content sensor using a fiber-type NIR spectrophotometer. Soil & Tillage Research, 80 171-183.

Viscarra Rossel, R. A, Walvoort, D. J. J., Mcbratney, A. B., Janik, L. J., Skjemsta, J. O. 2006. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. Geoderma, v. 131 (1-2) 59-75.