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SOIL ATTRIBUTES ESTIMATION BASED ON DIFFUSE REFLECTANCE SPECTROSCOPY AND TOPOGRAPHIC VARIABILITY

Julyane Vieira Fontenelli[1]; Lucas Rios do Amaral[1], José Alexandre Melo Demattê[2]; Paulo S. Graziano Magalhães[1]

[1] Department of Agricultural Engineering of the State University of Campinas, Campinas-SP, Brazil;
[2]Department of Soil Science, Escola Superior de Agricultura Luiz de Queiroz, Piracicaba-SP, Brazil

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Abstract. *The local management of crop areas, which is the basic concept of precision agriculture, is essential for increasing crop yield. In this context, diffuse reflectance spectroscopy (DRS) and digital elevation modelling (DEM) appears as an important technique for determining soil properties, on an adequate scale to agricultural management, enabling faster and less costly evaluations in soil studies. The objective of this work was to evaluate the use of DRS together with topographic parameters for quantification of soil physical and chemical properties and its relationship with the precision agriculture. For that, 34 soil samples were collected at 0-0.20 m depth, in an area of 100 ha, belonging to the Santa Fé mill, in Tabatinga, State of São Paulo, Brazil. After the soil collection, the samples were dried in a forced-air oven at 45 °C for a period of 24 hours, sieved through a 2 mm mesh, and sent to a soil-testing laboratory. Soil spectra were measured using a commercially available spectrophotometer FieldSpec 4, (Analytical Spectral Devices, Inc., ASD, Boulder, Colorado, USA) in the range of 350 2500 nm (Vis - NIR -SWIR), with three replicates for each sample. The topographic data were obtained from the DEM. Then, using radiometric information, regression* *models were generated by partial least squares (PLSR) to estimate the soil attributes. DRS shows a good correlation with copper, clay and H+Al (R^2 of 0.94, 0.93 and 0.65 and Relative Percent Deviation (RPD) of 4.80, 3.47 and 2.15, respectively) and with intermediate performance to predict Mn, sum of bases (SB), OM and base saturation (V%) (R^2 of 0.70, 0.65, 0.59 and 0.58, RPD of 1.65, 1.59, 1.58, 1.46, respectively). The physical and chemical soil properties vary along the slope, this differentiation was detected via electromagnetic spectrum. It appears that the DRS can assist in determining soil properties and knowledge of the soil spatial variability, adding new information to management practices in precision agriculture.*

Keywords. *soil spectroscopy, digital elevation model, directed sampling*.

Introduction

The adoption of management practices in precision agriculture (PA) allows you to improve the management of agricultural areas, through information of spatial and temporal variability of crops in order to improve the production performance of the culture, the rational use of inputs and the reduction of environmental impacts (Corá et al., 2004; Molin et al., 2010). Among the PA tools, the use of georeferenced soil sampling and the application of inputs to the variable rate is one of the main practices used in Brazilian crops (Cherubin et al., 2015).

However, to achieve the application of variable rate it is required adequate sampling of the soil physical and chemical attributes with high spatial resolution (Kerry e Oliver, 2007). Currently, conventional chemical analysis for characterization of soil attributes for high density sampling, they have proven costly and prohibitive. Most methods use large amounts of chemical reagents, which prolong the results of analyzes can promote impact on the environment (Souza Junior et al., 2011).

Thus, the cost and work associated with the increased sampling density for the characterization of soil properties for PA purposes are factors that limit the ability to represent the spatial variability of soil properties found in the field, which can lead to inadequate decisions because the spatial prediction error in the maps with low sample density increases the spatial variability, since inadequate application rates of lime and fertilizers are made.

Among the alternatives for the quantification of soil attributes for high density sampling, research has been directed to the use of techniques of diffuse reflectance spectroscopy (DRS). Most DRS studies in soils use measurements in the visible wavelengths (VIS), near infrared (NIR) and mid infrared (MIR) to predict the chemical and mineral composition of soils on field level and laboratory with appropriate scale to agricultural management, enabling faster and less costly evaluations in soil study (Fiorio et al, 2010; Cezar et al, 2013; Armenta and Guardia, 2014; Nocita et al, 2015). In this respect, Cozzolino and Moron (2003) and Dierke and Werban (2013) reported the use of spectrometer at the laboratory level for the estimation of various attributes such as soil texture, pH, organic carbon, potassium (K), calcium (Ca), magnesium (Mg), iron (Fe) and copper (Cu).

In addition, another technique that can be used to DRS to caracterize the spatial variability of the soil is the use of the digital elevation model (DEM), which determines aspects of the landscape. The

MDE constituted as an important tool through which relief attributes (elevation, slope and curvature) are derived and used to characterize the distribution of soil properties (Ziadat, 2005).

Thus, the importance of studies such as Gessler et al. (1995), which developed different statistical models to establish quantitative relationships between landforms derived from the DEM and the distribution of soil properties, can be observed. This approach is useful to determine the spatial variability of soil properties on an adequate scale to farm management, by providing better representation of gradual and continuous changes of soil properties, supporting faster and less costly evaluations in soil study (Zhu et al ., 2001).

However, it is necessary to establish an efficient and less costly method for the discrimination of physical and chemical characteristics of the soil in detail, to allow the use of PA to improve localized management of production areas. Thus, the objective of this work was to evaluate the use of DRS together with topographic parameters for quantification of soil physical and chemical properties and its relationship with the precision agriculture.

Materials and Methods

For this research it was necessary the acquisition of spectral and topographic information of the study area located at Usina Santa Fe, the city of Tabatinga, located in the central region of São Paulo, Brazil, for a total of 100 hectares. Thus, 34 sampling points for characterizing the spatial variability of the soil and relief (Figure 1) were demarcated. The geographical coordinates of the center point of the study area are located at 21 38 '12 "south latitude and 48 ° 39' 04" west longitude. The climate was classified as Aw (Koppen and Geiger, 1928), tropical rainy, cold and dry winter, with altitude ranging from 450 to 540 m. The soil use in the region is predominantly agricultural, highlighting the culture of sugarcane.

The soil samples were collected at layer 0 - 0.20 m of soil depth (horizon A), with the help of auger and georeferenced with GPS Trimble Juno 3B receiver. After the soil collection, the samples were dried in a forced-air oven at 45 ° C for a period of 24 hours and sieved through a 2 mm mesh. Then the samples were submitted to carry out physical and chemical laboratory analysis.

The granulometric composition of the soil was obtained by the method of the densitometer (Camargo et al., 196) and classified using the textural triangle according to EMBRAPA (2006) it was possible to distinguish two textural classes of soils: clayey (350-600 g kg^{-1} clay) and medium (150-350 g kg^{-1} clay). The analyzes of organic matter (OM), P, Ca, Mg, Mn, K, Al, H + Al, CEC, V%, SB, Cu, Zn, m% Fe, pH, were carried out according to Raij et al. (2001).

Soil spectra were obtained using a commercial spectrometer FieldSpec 4 (Analytical Spectral Devices, Inc., ASD, Boulder, Colorado, USA) with a spectral resolution of 1 nm at wavelengths of 350-1100 nm and 2 nm in lengths that range 1100-2500 nm, with three replicates for each sample. For this, we used a measuring device called the MugLight manufacturer, which has its own light source. In order to determine the reflectance factor, we used the standard plate 100% reflectance.

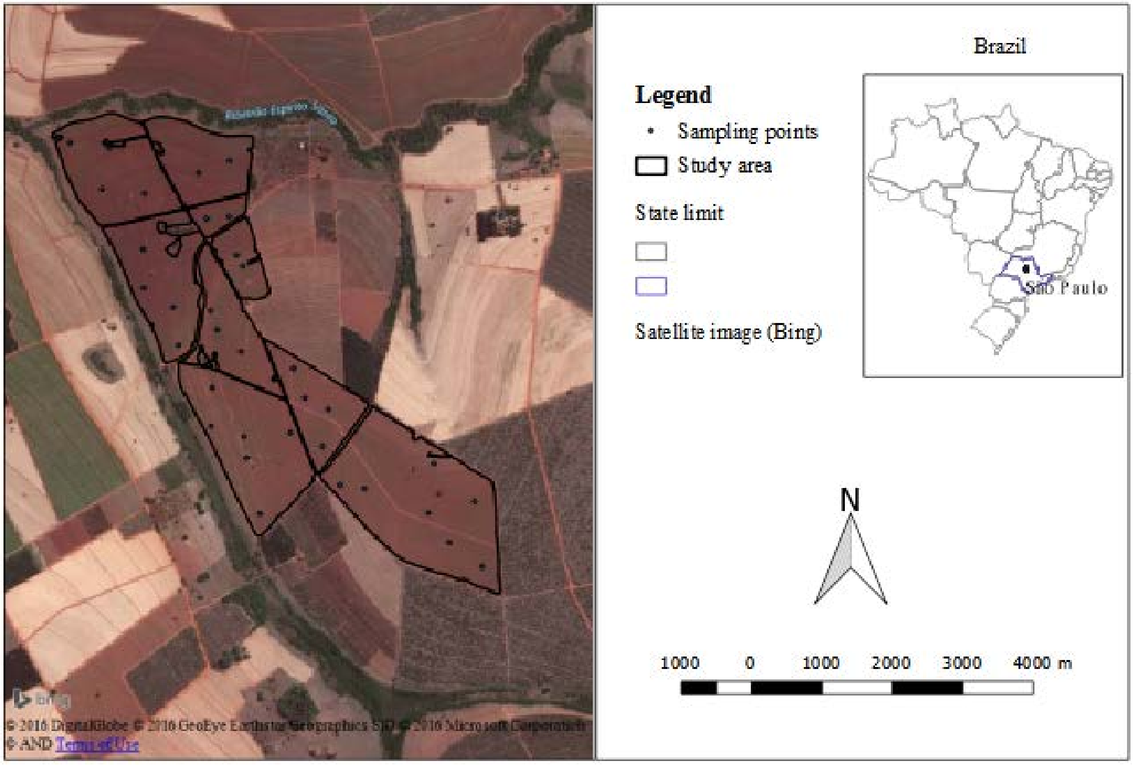

Figure 1 – Location of study area

Then, it was applied to the spectra pretreatments first and second derivatives Savitzky-Golay for offset correction and the spectra baseline slope for best regression models partial least squares (PLS) to predict the attributes soil, using Unscrambler software X® 10.2 (Camo AS, Oslo, Norway). The samples were randomly divided into a data set for calibration of the model (24 samples) and a group of data to the external validation (10 samples). The quality of the developed calibration was evaluated using the coefficient of determination (R^2), the mean squared prediction error (RMSEP) and RPD (Relative Percent Desviation).

According to Sayes et al. (2005), R^2 values between 0.50 and 0.65 indicate the possibility of discrimination of high and low concentrations in the model, while R^2 values from 0.66 to 0.80 indicates acceptable models, from 0.81 to 0.90 indicate good models, and finally, values greater than 0.9 indicate excellent model prediction capability. According to Dunn et al. (2002) and Chang et al. (2001) RPD values above 2.0 are considered excellent models, 1.4 to 2.0 acceptable models and less than 1.4 untrusted models. The use of R^2 and RPD figures of merit are the most important indicators for assessing the quality of the analysis by diffuse reflectance spectroscopy (Williams, 2001).

The DEM were obtained in two ways: DEM - SRTM, SRTM data (Shuttle Radar Topographic Mission) obtained by synthetic aperture radar interferometry in the USGS database (United States Geological Survey) in 1 format 'arcossegundo (~ 30 m) horizontal resolution, datum WGS84, over 74,418 listed points obtained from the GPS receiver. The MDE - TOPODATA obtained from the refinement of the original SRTM data for Brazil (Valeriano and Rossetti, 2009) with spatial resolution of 30 m, over 74,418 listed points obtained from the GPS receiver.

The DEM represents continuously terrain elevation values through a regular grid coordinates x, y and z values, elevation, (Demattê et al., 2014). To model processing, it was used the software ArcGis (ESRI, 2010), with function of Application top to Raster 3D Analyst module. From the MDE, the results are the slope maps, aspect and curvature. In addition, DEM were designed for UTM coordinates (Universal Transverse Mercator) Zone 22 South and the Reference Geodetic System -

Datum SIRGAS 2000.

The soil sampling points were specialized in computing environment, obtained topographic point information of each index. Thus, there was Pearson correlation with the results of chemical and physical analysis laboratory and topographic attributes.

Thus, the DEM - SRTM and DEM - TOPODATA were evaluated according to the ability to derive attributes of the land that best correlates with soil properties.

Results and Discussion

Soil analyzes from the surface layer (0-0.20 m) indicate high variability of the chemical and physical soil properties, due to heterogeneity of soil formation processes, as well as intensive agriculture with high input of lime and fertilizer the soil (Table 1). This explains the high levels coefficient of variation of phosphorus (P), aluminum saturation (m%), copper (Cu), aluminum (Al), respectively 103.70; 109.29; 97.06 and 87.23%. Furthermore, there is a high concentration of copper on the surface layer of soil (5.5 mg kg^{-1}).

The soils of the featured region, characterized as being of medium texture to clayey (EMBRAPA, 2006) have the greatest potential to retain copper accruing from the management practices of culture, in view of the higher organic matter (OM) and cation exchange capacity (CEC).

The average base saturation is less than 50%, indicating that the study area soils are medium to low fertility. In addition, low values of aluminum saturation (m%) were observed in the surface soil layer. This can be explained considering that areas with high application correctives (limestone) tend to occur elevation V%, which displaces the Al^{3+} to the soil solution and then leached into subsurface layers of soil and hence reduces m% in the region of 0-0.20 m (Raij, 1969).

Table 1 - Chemical and physical characteristics of soil samples used in this study.

Variable	Min.	Max.	Mean	SD[1]	CV[2]
Clay (g kg^{-1})	212.00	494.00	321.70	94.08	29.24
OM[3] (g kg^{-1})	10.00	25.00	16.70	4.88	29.22
pH ($CaCl_2$)	4.30	6.00	5.02	0.48	9.56
P (mg kg^{-1})	4.00	52.00	10.00	10.37	103.70
K ($mmol_c$ kg^{-1})	0.26	2.33	1.10	0.45	40.91
Ca ($mmol_c$ kg^{-1})	4.62	32.45	13.84	7.23	52.24
Mg ($mmol_c$ kg^{-1})	3.36	13.32	7.01	2.88	41.08
Al ($mmol_c$ kg^{-1})	0.27	3.55	0.94	0.82	87.23
H+Al ($mmol_c$ kg^{-1})	13.00	39.00	23.05	6.60	28.63
SB[4] ($mmol_c$ kg^{-1})	9.11	47.47	21.95	9.96	45.38
CEC[5] ($mmol_c$ kg^{-1})	32.59	68.47	45.01	9.81	21.80
V[6] (%)	22.60	69.33	47.62	14.56	30.58
m[7] (%)	0.75	28.04	5.49	6.00	109.29
Cu (mg kg^{-1})	0.30	5.50	1.70	1.65	97.06
Mn (mg kg^{-1})	1.10	15.10	4.87	3.23	66.32
Fe (mg kg^{-1})	4.00	26.00	11.23	5.12	45.59
Zn (mg kg^{-1})	0.20	0.50	0.32	0.06	18.75

[1]Standard deviation; [2]Coefficient of variation; [3]Organic matter; [4]Sum of bases; [5]Cation exchange capacity; [6]Base saturation; [7]Aluminum saturation.

According to Table 2, it can see some trends among the correlations. It was noted that the relationship between the chemical, physical soil properties, and topographic attributes vary for each digital elevation model lineate. It has, for example, to the DEM - TOPODATA a curvature of correlation with OM, SB and CEC and V% higher than the same attributes as the MDE - SRTM.

Moreover, in terms of absolute values, the DEM - TOPODATA showed generally higher correlations of topographic indexes with soil properties. According to Hofton et al. (2006), the SRTM data can present distortions in altimetry due to the soil use and land cover, especially dense vegetation and buildings, which often prevents the determination of elevation attributes, curvature, aspect and slope nearest values obtained in field .

In terms of elevation attribute, there is a correlation with the clay of -0.409 and -0.363 for DEM-TOPODATA and DEM-SRTM respectively. Demattê et al. (2014) developing a soil limits detection method through the interaction of spectral data and landforms from DEM prepared by contour lines with vertical equidistance of 20 m, observed correlation between the elevation and the clay content in six toposequence ranging from -0.187 to -0.989. Graham & Buol (1990) points out that this fact is associated with the variation of the source material and weathering action.

Thus, there is a potential for the use of derivatives topographic attributes of digital elevation models for knowledge of the spatial variability of soil attributes. The DEM can be used as an external variable in the mapping of soils.

Table 2 – Matrix of Pearson correlation between the chemical and physical attributes of the soil and topographic indices (elevation, curvature, aspect e slope)

	MO	SB	CTC	V%	Clay
			DEM - TOPODATA		
Elevation	-0.288	-0.116	-0.251	-0.039	-0.409
Curvature	-0.576 to	-0.439	-0.556	-0.225	-0.444
Aspect	-0.184	-0.103	-0.253	0.047	-0.276
Slope	0.227	0.309	0.386	0.074	0.068
			DEM - SRTM		
Elevation	-0.261	-0.148	-0.244	-0.078	-0.363
Curvature	-0.027	0.099	0.169	-0.043	-0.007
Aspect	-0.038	0.232	0.089	0.267	-0.084
Slope	0.117	0.143	0.196	0.014	0.061

The DRS showed to be more efficient in the application on precision agriculture, especially the quantification of copper content, clay and H + Al (R^2 of 0.94, 0.93 and 0.65 and RPD 4.80; 3:47 and 2:15, respectively) with intermediate performance for predicting Mn, SB, MO and V% (R^2 of 0.70, 0.65, 0.59 and 0.58, RPD 1.65, 1.59, 1.58, 1.46, respectively) according to the classification (Dunn et al. 2002; Chang et al., 2001), Table 3.

In the case of clay content and copper (Cu), the best model fit is related to the greater amount of these attributes in the soil (Table 1), thereby providing greater interaction between electromagnetic energy and particles of clay, as well as interactions energy with the molecular bonds of copper.

According to Sousa Junior et al. (2011), clay content has absorption features, characteristics in the regions of the visible and near infrared of the electromagnetic spectrum, so the higher the better clay fraction are the chances of success of quantification models.

The poor prediction of attributes (Al, Fe, P, Zn, K, Ca, CEC, pH and Mg) performance of the models makes it clear the heterogeneity of the area and the difficulty of building models with lower sampling density (24 calibration samples) without prior knowledge of the spatial variability of soil attributes.

Thus, best results were obtained when secondary information of plant and soil is used for targeted soil sampling for model calibration (Wetterlind et al., 2010).

Table 3 - Statistical evaluation of estimation models applied to the calibration attributes samples (internal test) and model validation samples (external test)

Variable	Pretreatments	Calibration		Validation			
		RMSE	R^2	RMSE	R^2	RPD	PLS Factors
Al	SG[1]-1ª derivative	0.5482	0.6434	0.9316	0.0544	0.88	5
Clay	Absorbance	19.5579	0.9581	27.1386	0.926	3.47	5
Ca	Absorbance	3.692	0.7027	5.9851	0.2786	1.21	6
CEC	SG-1ª derivative	4.0383	0.8126	7.3177	0.435	1.34	4
Cu	SG-1ª derivative	0.1267	0.9911	0.345	0.9398	4.78	6
Fe	Absorbance	4.8904	0.2049	5.2328	0.1639	0.98	3
P	SG-1ª derivative	0.3308	0.9981	7.2129	0.1906	1.44	12
H+Al	Absorbance	1.8791	0.8577	3.0751	0.6501	2.15	7
m%	SG-1ª derivative	1.2397	0.9296	4.4133	0.181	1.36	7
Mg	SG-1ª derivative	0.3068	0.9899	2.3704	0.4497	1.21	9
MO	Absorbance	2.847	0.6162	3.0894	0.585	1.58	2
Mn	SG-1ª derivative	0.3815	0.9878	1.9607	0.7049	1.65	8
pH	Absorbance	0.2546	0.7003	0.3698	0.4194	1.30	6
K	SG-1ª derivative	0.2729	0.6901	0.4424	0.2519	1.02	5
SB	Absorbance	4.3277	0.8198	6.2776	0.6519	1.59	5
V%	Absorbance	6.7653	0.7892	10.004	0.5767	1.46	6
Zn	SG-1ª derivative	0.045	0.5561	0.0619	0.228	0.97	3

[1]Savitzky-Golay

The study area has altitude ranging from 460 to 530 m (Figure 2A). The clay content vary along the slope (Figure 2B, 2D). This differentiation was detected by the electromagnetic spectrum two point soil samples collected at different locations in topossequence (Figure 2C). Such variations can assist in points demarcation programs for sampling and analysis of soil via spectroradiometry adding new information to the precision agriculture.

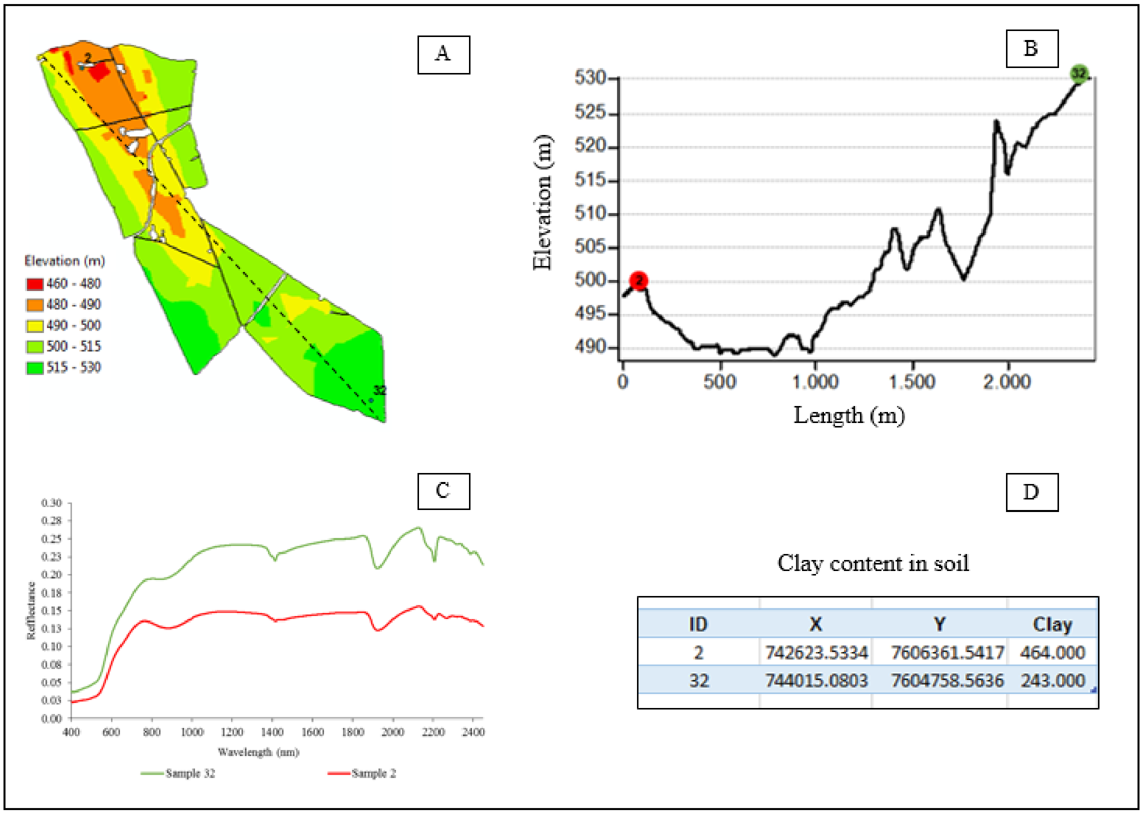

Figure 2 - Spatial distribution of variability of altitude in the study area (A); (B) Graphical representation of toposequence; (C) spectral curve and (B) clay content of two soil samples collected in regions of different altitudes.

Conclusion or Summary

The spectroradiometry diffuse reflectance was efficient in determining the contents of clay, copper (Cu) and aluminum more hydrogen (Al + H), indicating that the spectral response of these soils can be used to establish the levels of these attributes.

The DEM-TOPODATA showed the highest correlations between topographic attributes and soil properties. The curvature and the elevation were the topographic indexes that best correlated with the chemical and physical soil properties in both digital elevation models.

Thus the topographic attributes derived from digital elevation models can be used to characterize the spatial variability of soil properties in large scale, assisting in directing the sampling and soil analysis spectroradiometry adding new information to management practices in precision agriculture.

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