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Mineralogical, and Spectral Characterization of Soils in the Passo da Pedra River watershed, in the southwest of the State of Paraná, Brazil

Elisete Guimarães[1], Júlio Caetano Tomazoni [2], Elis Suzane Antes[3], Juliane Mônica Ruthes[4]
[1]Professora da UTFPR Campus Francisco Beltrão, do Curso de Engenharia Ambiental – guimaraes@utfpr.edu.br
[2]Professor da UTFPR Campus Francisco Beltrão, do Curso de Engenharia Ambiental – caetano@utfpr.edu.br
[3]Acadêmica do Curso de Engenharia Ambiental, da UTFPR Campus Francisco Beltrão – elissantes@hotmail.com
[4]Acadêmica do Curso de Engenharia Ambiental, da UTFPR Campus Francisco Beltrão – julianeruthes@yahoo.com.br
Autor para correspodência

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ABSTRACT
This work is an investigation of the spectral behavior of soils, which occur in the Passo da Pedra River watershed, in the southwest of the State of Paraná, Brazil. In the survey, data was used chemical, textural, and spectra obtained in the laboratory and remote sensing. The results indicate that the laboratory spectral responses are influenced by texture, organic matter content, and the mineralogical characteristics of the soil. It was verified that the organic matter, interference from cultural remains, and relief type, directly influences the spectral data of the CCD sensor.

Keywords: Spectral behavior of soil; principal components analysis; spectroscopic methods; satellite data.

Introduction

According to Lal (2007), the main global issues of the 21st century include food insecurity and hidden hunger, global warming and carbon sequestration, water scarcity and eutrophication, soil degradation and desertification, Should this be with the "current conditions" energy scarcity and biofuels. The solution for many of these issues depends to a great extent on sustainable management of world soils.

Brazil covers half of the area of South America and has a large spatial diversity in terms of climate, geology, geomorphology, and pedology. The country extends in a north-south direction and has a dominantly tropical climate, except the southern 20% of the country, which has predominantly mesothermal subtropical climates. Within this large territory, large amounts of agricultural and livestock-related activities have made the country among the world's large producers. This good agricultural performance has become more evident with the development of technology-intensive agriculture, including the increase of biofuel (bioethanol, biodiesel, and bioelectricity) production (Ritter, 2007). To ensure continuous agricultural development, Brazil should invest in research that will provide data about its natural ecosystems, in which soils are a special issue.

The study of soil is complex, and conventional assessment methods are slow, expensive, and not very diversified. Therefore, it is necessary to develop and/or to improve techniques and methodologies to overcome these limitations.

One of the most important alternatives is the application of remote sensing technology based on the spectral analysis of soils from data collected from spectroradiometers in laboratory conditions and from different airborne and orbital sensors. Galvão et al. (1998), Ben-Dor et al. (2002), and Demattê (2004, 2005) have explored remote sensing to access chemical, mineralogical, and structural characteristics of soil.

The need for rapid and inexpensive techniques for soil characterization to support precision agriculture has become an important issue, particularly in countries like Brazil, whose agricultural lands are dominated by large fields (Mouazen et al., 2007). Agro-ecological management decisions (e.g., precision agriculture) have led to the use of modern technologies and, in particular, those based on remote or in-situ reflectance spectroscopy (DU, C. et al., 2007).

A deeper understanding of the spectral properties of soils, based on data collected in the laboratory, may contribute to future research involving the use of data collected from satellites (Islam et al., 2003, 2005; Demattê, 2004, 2005).

Among the various methods for studying soil, those using radiometric techniques deserve emphasis as they are the most used methods in biological and physical-chemical research (Brown et al., 2005).

Radiometry is, by definition, a quantitative measure of the intensity of any of the known types of radiation, such as electromagnetic radiation, emitted by the sun or an artificial source such as a lamp. When electromagnetic radiation is designated "optical", it implies that it is limited to the region of the electromagnetic spectrum of wavelengths from visible to the infrared, short wave, i.e., from 400 to 2500 nm (or, 0.4 μm to 2.5 μm), which can be reflected by surfaces of objects in accordance with the laws of optical reflection (Menezes & Netto, 2001).

Spectral radiometry is one of the most important areas of remote sensing. This is because field or laboratory measurements show the intensity with which each material (i.e., a type of rock or vegetation) reflects the electromagnetic radiation at different wavelengths, and these measurements explain how each of these object types will appear in images (Menezes & Netto, 2001).

Soil properties derived from spectra were studied long before the 1980s. Many studies have focused on the visible and infrared regions of the spectrum (between 0.4 and 2.5 μm), with some studies focused on data in the thermal and microwave regions (Luleva, 2007).

There has been growing interest in the use of diffuse infrared reflectance as a tool for rapidly analyzing the physical-chemical and mineralogical characteristics of soils (Brown et al., 2005).

At the same time, chemometry analyses have been developed, as well as other tools for use in the spectral characterization of soils (Islam, 2005; Brown et al., 2005; Rossel, 2006). “Unsupervised methods of multivariate statistics, such as hierarchical cluster analysis (HCA) and principal component analysis (PCA), take into account the correlations among several variables that are simultaneously analyzed, thus allowing the interpretation of better-summarized information. Sena et al. (2002) besides, since these methods do not need prior information given beforehand, no explicit soil information is used.

In the visible spectrum (VIS; 400-700 nm), the information concerning soils and minerals is characterized by a broad band, typical of electronic transition processes. In the near (NIR; 700-1100 nm) and short wave (SWIR; 1100–2500 nm) infrared spectra, are characterized by absorptions attributed to band combinations and to hues of fundamental processes (Ben-Dor et al., 2002).

The main objective of this investigation is to characterize physically, chemically, mineralogically, and spectrally different soils from Passo da Pedra River watershed in Paraná State, Brazil, using data collected in the laboratory and remote sensing.

Materials and Methods

The research was carried out in the watershed of the Passo da Pedra River (Figure 1), located in the Pato Branco municipality in the southwest of the State of Paraná, Brazil. The watershed has an area of 15.9 km^2.

Physiographical Characterization

The regional climate, according to the “Köeppen” system, is Cfb or, in other words, mesothermal super humid. In geological terms, the watershed is made up of basaltic rock from the São Bento Group, Serra Geral Formation. Rocks are either of tholeitic basalt with intercalated sandstone or acidic volcanic rocks, both of which are intercalated with diabasic dikes and sills. The relief is undulating, and, under these conditions, the action of climate and vegetation on the region's geology has led to the formation of deep, well-drained clay soils.

In the watershed, as illustrated in detail in Figure 1, ten sampling sites were identified. The sites had dimensions of 8 x 8 pixels from CCD – Band sensors 1 through 5 (spatial resolution 20 m), or 160 x 160 m, for a total area of 25,600 m^2 for each site, under different relief conditions and types of soil.

The sampling sites were georeferenced, and 10 soil samples were randomly collected from each of them at a depth of 0 to 20 cm. These were grouped into a single sample that represented the average for the specific sampling site. The 10 samples included the following types of soil: sample 1LVd, dystrophic Red Latosol; sample 2RU, Fluvic Neosol; sample 3NVd, dystrophic Red Nitosol; sample 4LVd, dystrophic Red Latosol; sample 5LVd, dystrophic Red Latosol; sample 6NVd, dystrophic Red Nitosol; sample 7LVd, dystrophic Red Latosol; sample 8LVd, dystrophic Red Latosol; sample 9RL, Litholic Neosol; and sample 10CX, Haplic Cambisol.

In the laboratory, the samples were quartered, dried, ground, sifted in a 2 mm sieve, homogenized, and stored in cardboard boxes. The samples were subjected to the analyses described below.

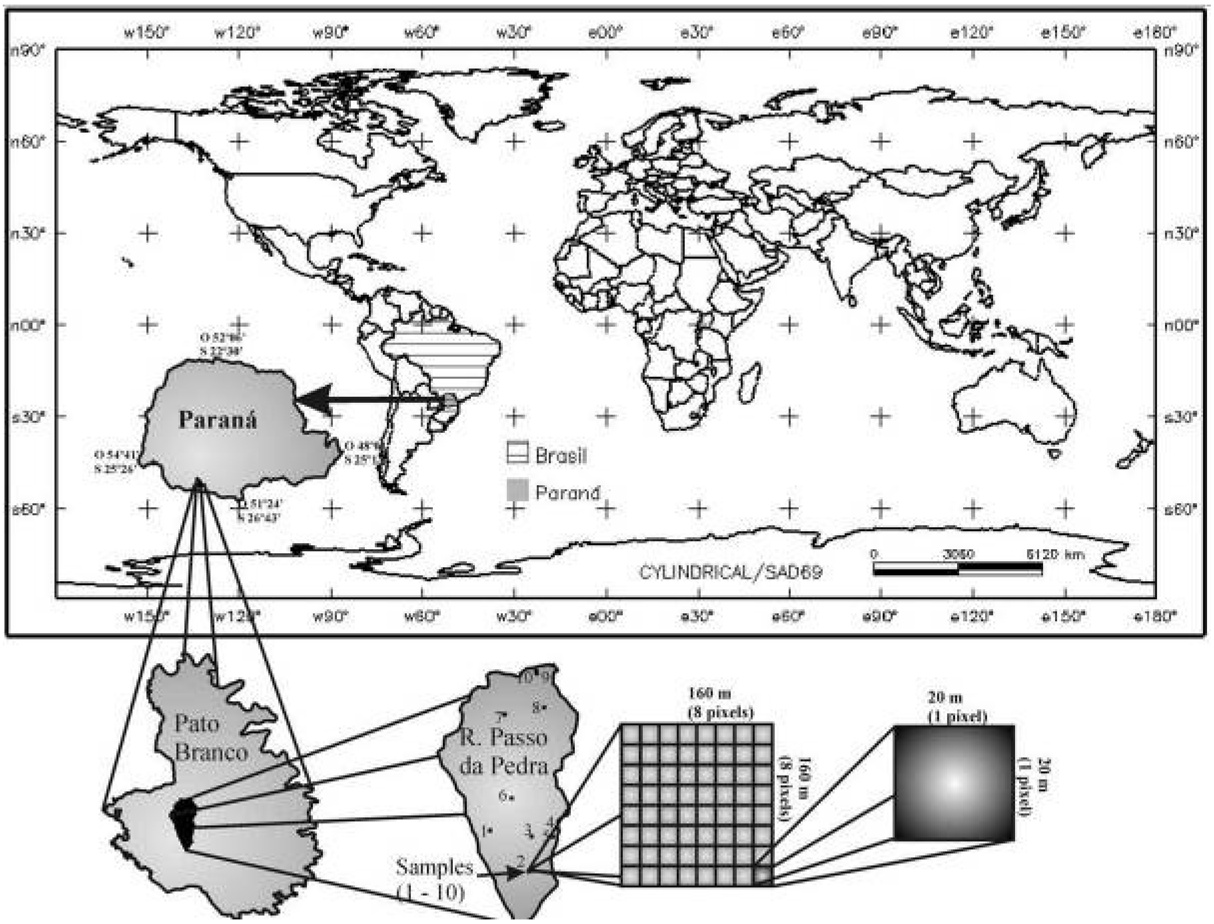

Figure 1 - Map highlighting Brazil, the State of the Paraná, the Municipality of Pato Branco, the Passo da Pedra River watershed, and the shape of the sampling sites.

Soil sampling and laboratory analyses.

Chemical analyses - The organic matter was quantified by determining the soil's organic carbon by wet oxidation using the Walkley-Black method (Pavan & Miazawa, 1996). The analyses were carried out at the laboratory of the UTFPR and IAPAR - Agronomic Institute of the Paraná.

Physical analysis for determining soil fractions - The ten samples were air-dried, broken up manually, and passed through a sieve with a 2 mm screen opening (9 mesh) to obtain an air-dried fine soil (ADFS). Granulometric analysis of the ADFS was carried out according to conventional procedures for the UTFPR/IAPAR laboratory, following the systematic proposed by EMBRAPA (1997).

Spectral analyses of diffuse reflectance ultraviolet-visible spectroscopy (DRUV-VIS), in Laboratory - The spectra were recorded at room temperature in a Shimadzu UV-2401PC spectrophotometer (190 - 900 nm) equipped with a 240-52454-01 integration sphere accessory. Data analysis was performed at the laboratory LABPAM - Laboratory Projects and Environmental Processes of DQ/UFPR. For the diffuse reflectance infrared spectroscopy with Fourier transform (DRIFT), the spectra were recorded in an EXCALIBUR model BIORAD FTS 3500GX spectrophotometer (2 cm^{-1}/256 scans, 1550 - 3000 nm). For the DRIFT measurements mode, the Gemini Diffuse Reflectance Sampling Head accessory was used. Data analysis was carried out at the Chemistry Department at the DQ/UFPR. X-Ray Diffractometer (XRD) data analysis was performed at the DQ/UFPR. X-ray diffraction analysis, by the powder method, was carried out with a Shimadzu XRD-6000 diffractometer with a copper electrode, with K-alpha copper radiation (Cu-Kα, average wavelength = 1.5418 A°) and a source voltage and current of 40 kV e 40 mA, respectively, sweeping from 3° to 70° with a goniometer speed of 20 θ min^{-1}. X-Ray Fluorescence (XRF) analyses were carried out at the Laboratory for Analysis of Minerals and Rocks (LAMIR) of the Geology Department/UFPR, with the quantification of the Fe_2O_3, Al_2O_3, SiO_2, and TiO_2 oxides of the soil by means of a PHILIPS ANALYTICAL model PW 2400/00 X-Ray Fluorescence System equipped with a 2510 Sample Changer.

Soil sampling orbital data

The soil sampling sites were spectrally characterized through images from the CCD sensor of the satellite CBERS 2b. The first step was to select the most adequate image from scene 160/129, which covers the basin, for evaluation of the spectral samples of the sampling sites. The samples were collected in the month of August. The sensor (CCD) performs the scan space through a matrix of detectors installed inside the satellite, capturing an entire scene as the platform moves in space (Ponzoni et al., 2007).

By using the SPRING (System for Processing Georeferenced Information) 5.2.3 software package (INPE, 2013), a database was created for the Passo da Pedra river watershed in the UTM and SAD-69 coordinate systems for receiving images from the sensor.

To correct atmospheric effects, the SCORADIS (Radiometric Correction System for Satellite Images) computer program was used (Zullo, 2006), which is an application developed by the Center for Meteorological and Climactic Studies Applied to Agriculture at the State University of Campinas, Sao Paulo, Brazil (CEPAGRI/UNICAMP). This computer program has as its objective the application of the 5S model (*Simulation du Signal Satellitaire dans le Spectre Solaire*) for atmospheric correction (Zullo et al., 2006). The SCORADIS system was adapted for processing data from the CCD sensor, including the conversion from digital level (DL) values of the images to values for the apparent and surface bidirectional reflectance factor (BRF).

Results and Discussion

For the interpretation of the spectral responses from the ten samples (Figure 1), the physical-chemical (Table 1) and mineralogical (Figure 2) data were considered.

Figure 2 shows the X-ray diffractograms for all of the soil samples. Dolomite, $CaMg(CO_3)_2$, is present in soil sample 1LVd (Figure 2). This mineral is present because of the soil correction (for agricultural activity) that was carried out with dolomitic limestone a few months before the sample collection.

Kaolinite, $Al_2Si_2O_5(OH)_4$, and gibbsite, $Al(OH)_3$, are present in all samples (Figure 2). Quartz, SiO_2, is present in the 10 samples studied. It is part of the detritus, of the sand fraction, specifically.

Hematite, Fe_2O_3, is present in all 10 soil samples (Figure 2). This mineral is common in the soils of the watershed because of the subtropical warm and humid climate and well-drained soils. Goethite, FeOOH, appears in samples 1LVd, 2RU, 3NVd, 4LVd, 7LVd, and 8LVd. Magnetite, Fe_3O_4, appears in samples 5LVd, 6NVd, 7LVd, 8LVd, and 9RL (Figure 2).

Table 1 – Spectral ranges of the CCD sensor and corresponding bands in the laboratory spectra.

Bands of the CBERS 2b			Bands of the spectra		
BAND	Interval (nm)	Average (nm)	Spectra	Interval (nm)	Average (nm)
CCD1	450 – 520	485	S1	450 – 520	485
CCD2	520 - 590	555	S2	520 – 590	555
CCD3	630 – 690	660	S3	630 – 690	660
CCD4	770 – 890	830	S4	770 – 850	830

Legend: CCD1 to CCD4 – CCD sensor bands from the CBERS-2b satellite. Spectra – The data from spectra (S1 to S4) and bands from the CCD sensor are represented by the mode of the reflectance values.

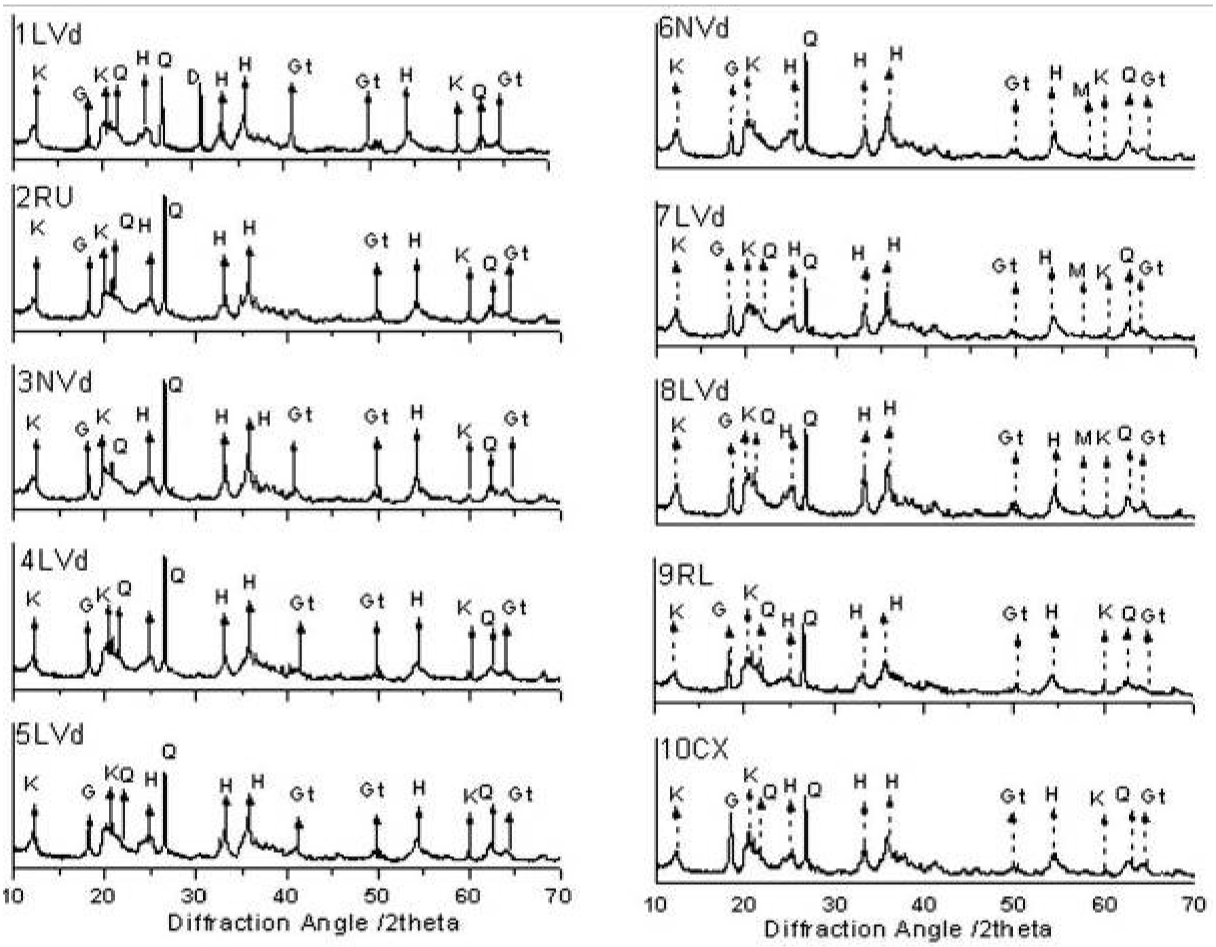

Figure 2 - Diffractograms of soils from the Passo da Pedra River basin and interpretation.

Samples 2RU, 3NVd, 7LVd, and 8LVd (Figure 2) contain rutile, TiO_2, which is from the decomposition of basaltic rock and is present mainly in the sand and silt fractions.

Figure 3 displays the DRUV-VIS and a part of the near infrared spectra. The OM causes strong absorption, reducing the reflectance throughout the entire spectral range analyzed (220-850 nm). The OM contains reactive groups of carboxylic (R-COOH) and phenolic (Ø-OH) compounds, which dissociate and release H^+, which contributes to soil acidity. The most striking effect of the absorption caused by OM can be observed in Figure 3 in the spectra for soils 4LVd, 6NVd, 9RL, and 10CX and in Table 2 since both display the highest levels of this organic component.

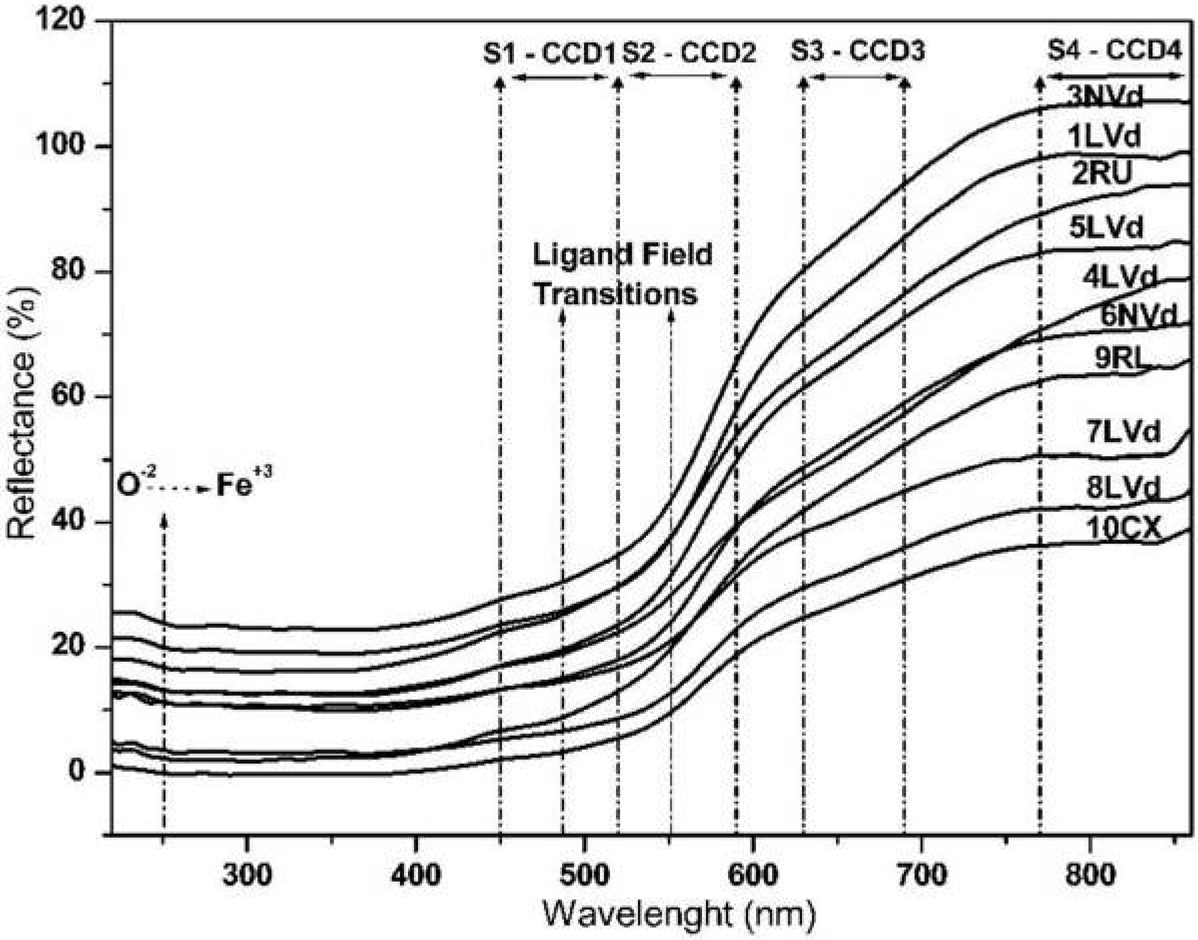

Figure 3 - Spectra ranging over the visible and infrared regions of soils from the Passo da Pedra River watershed, with emphasis on the range of spectral bands from CBERS 2b.

In the soil samples with clay-like textures, the OM joins with the clay fraction to form more stable compounds, which tend to absorb energy, reducing reflectance. Soil 7LVd (Figure 3) has low reflectance because it is influenced by the characteristics mentioned above as well as by the iron oxides.

The minerals, the ferric oxide ion, the water, and the hydroxyls are the most important components in determining features in the reflective range of the spectrum (220 to 2,575 nm). The iron oxides and hydroxides (hematite and goethite) are common in tropical soils and were detected in the X-ray diffractograms of the ten studied soil samples.

The high levels of iron reduce the reflectance of all soil samples, mainly samples 7LVd, 9RL, and 10CX, throughout the entire spectrum (220 - 850 nm) (see

Figure 3 and Table 2). A feature near 485-550 nm (Figure 3) is assigned to the $^6A_1 + ^6A_1 \rightarrow ^4T_1(^4G) + ^4T_1(^4G)$ excitation of an Fe-Fe pair into hematite structure, while the band near 650 nm corresponds to the $^6A_1 \rightarrow ^4T_1(^4G)$ transition of the goethite and hematite structures. Higher energy features, at wavelengths above 250 nm, are assigned to ligand-to-metal charge-transfer transitions (LMCT) into iron oxide structures ($O^{2-} \rightarrow Fe^{3+}$) (Sherman and Waite, 1985; Fukamachi et al., 2007).

The texture characteristics also interfere in the spectral responses of the soils. In the samples with higher levels of silt and sand, there is a tendency to reduce the interference, especially from the OM, increasing the spectral response. For samples 1LVd, 2RU, 3NVd, and 5LVd, which display similar values for OM (intermediate values), however, the silt and sand content are significant, and the spectral responses are high.

In the infrared region (Figure 4), spectra were recorded starting from 1,666 nm (6,000 cm^{-1}) to 2,670 nm (3,750 cm^{-1}).

The spectral responses shown in Figure 4 are strongly influenced by the OH-, water, kaolinite, and gibbsite structures. The organic matter is spectroscopically active throughout the entire VIS and NIR region; however, the chemical complexity of organic matter makes it difficult to assign specific absorption bands to particular wavelengths (Rossel, 2006).

In the range from 1,900 to 1,950 nm (Figure 4), there is a pronounced concavity in the spectra due to the presence of kaolinite, water, and OH- groups ($\nu + \delta$ de O-H) (Meneses, 2001; Demattê, 2005; Rossel, 2006). The effects of these components are more pronounced in soils 4LVd, 6NVd, 5LVd, and 8LVd.

In the region centered on 2,200 nm, all spectra have an interval with strong energy absorption, which is the main region of manifestation of kaolinite (Rossel, 2006). Gibbsite has its absorption features in the range from 2,250 to 2,279 nm, and it stands out well in all soils except 2RU, 3NVd, 4LVd, and 6NVd (Figure 4), which are less-weathered soils (Meneses, 2001; ROSSEL, 2006).

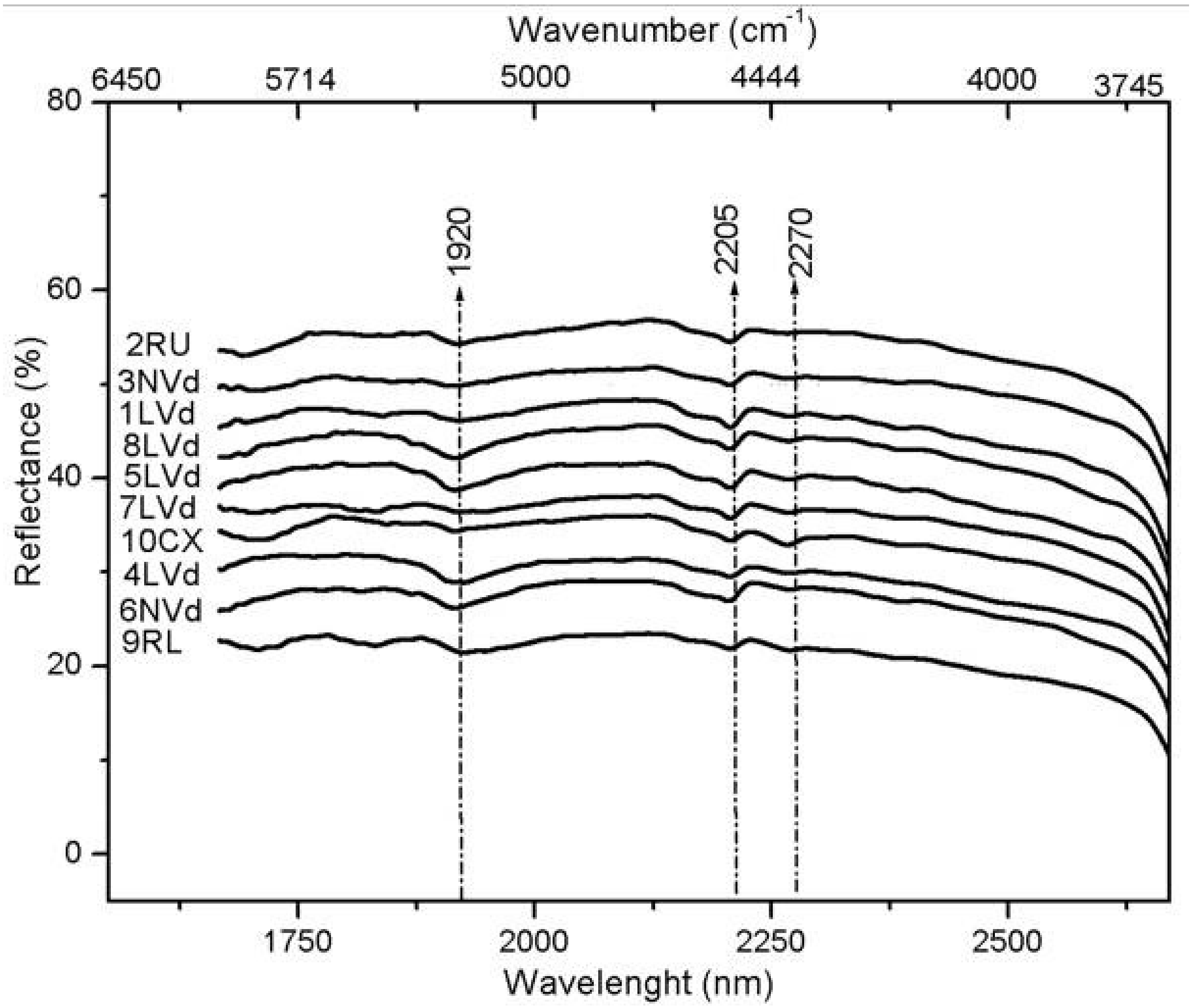

Figure 4 - Spectra ranging over the infrared region of soils from the Passo da Pedra River watershed.

To construct the relationships between the laboratory spectral data, physical-chemical analyses, and satellite data (Table 2), the PCA exploratory method was used. The data were evaluated in two matrices composed of ten samples by twelve variables.

Table 2 – Physico-chemical analyses and spectral data, both orbital and from laboratory, of the soils from the passo da pedra river watershed.

Variable		Samples									
		1LVd	2RU	3NVd	4LVd	5LVd	6NVd	7LVd	8LVd	9RL	10CX
Chemical Physical	OM (%)	4,02	4,69	4,02	8,04	4,02	4,69	3,35	3,35	6,70	5,36
	Clay (%)	32,00	38,00	29,00	32,00	39,00	47,00	55,00	59,00	22,00	29,00
	Sand (%)	27,00	23,00	19,00	24,00	21,00	14,00	17,00	11,00	32,00	21,00
	Silte (%)	41,00	39,00	52,00	44,00	40,00	39,00	28,00	30,00	46,00	50,00
Fluoresce nce data	SiO2 (%)	29,60	33,10	34,00	30,70	31,60	31,70	28,90	31,00	29,20	26,80
	Al_2O_3 (%)	21,90	21,30	22,70	21,70	24,00	24,90	24,00	25,60	21,60	25,80
	Fe_2O_3(%)	18,90	18,30	18,70	17,90	18,90	16,90	21,60	18,00	21,80	19,70
	TiO_2 (%)	4,80	5,90	6,50	4,90	5,70	4,70	5,10	4,60	6,30	5,40
Spectra	S1	15,00	17,00	16,00	13,00	15,00	13,00	9,00	8,00	12,00	7,00
	S2	21,00	25,00	24,00	20,00	22,00	18,00	12,00	11,00	19,00	11,00
	S3	72,00	60,00	78,00	46,00	61,00	55,00	39,00	34,00	56,00	34,00
	S4	89,00	86,00	95,00	70,00	81,00	69,00	45,00	45,00	69,00	41,00
Ban ds	CCD1	15,00	6,00	7,00	7,00	8,10	12,50	10,00	14,00	9,00	9,00
	CCD2	20,00	11,00	12,10	12,00	15,00	16,60	17,00	21,00	14,00	14,00

	CCD3	30,00	19,50	18,00	17,50	22,00	27,00	26,00	32,00	19,00	19,00
	CCD4	38,82	30,37	27,90	26,43	31,75	35,68	33,22	42,44	30,78	30,99

Legend: CBERS 2 sensor – CCD; OM – Organic Matter; Spectra – The data from spectra (S1 to S4) and bands from the CCD (CCD1 to CCD4) sensor are represented by the mode of the reflectance values.

The Principal Component Analysis (PCA) method was performed by using the PLS-Toolbox Module from the Matlab 6.5 software package (Mathworks, 2006).

The first matrix contains the physical-chemical analyses and the spectral data obtained in laboratory.

The ten samples are characterized by different types of soil under the handling of direct seeding. The twelve variables are composed of textural data (sand, silt, and clay), chemical data (OM, Al_2O_3, Fe_2O_3, SiO_2 and TiO_2), and spectral data obtained in the laboratory in the VIS (450 - 850 nm) and NIR (1650 – 2650 nm) regions. These regions correspond to the intervals of the spectral bands of the CCD sensor. These variables were chosen due to their direct interference regarding the spectral responses of the soils.

The data treatment revealed 9 PCs (Table 3) for a total of 100% of the accumulated variance. From this set, 5 PCs were separated for the evaluation of the data set, and these 5 PCs accounted for 98.48% of the variance.

Table 3 – Principal components (PCA) and percentage participation in the evaluation of the spectral data (laboratory).

PC	% of PC	% of accumulated variance
1	51.14	51.14
2	24.68	75.82
3	10.12	85.93
4	8.25	94.19
5	4.30	98.26
6	0.78	99.26
7	0.50	99.76
8	0.21	99.97
9	0.03	100.00

Figure 5 shows that PC1 is responsible for the differentiation between soils with higher and lower spectral responses.

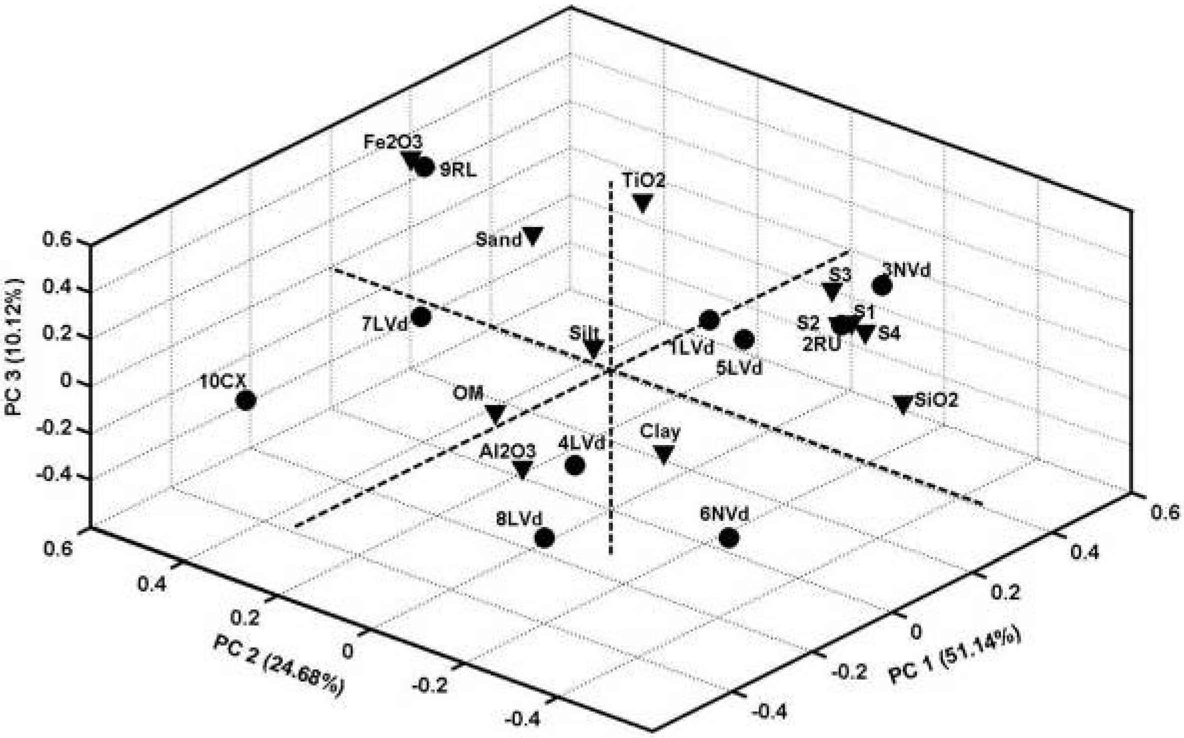

Figure 5 – Scatterplot of Principal Components (PC1 x PC2 x PC3) of the spectra.

In the positive quadrant, soils 1LVd, 2RU, 3NVd, and 9RL are associated whit the spectra (ECCD1 – ECCD4), and the variables sand, silt, and SIO_2 increase the spectral response. Soil 9RL is in this quadrant due to the sand and silt proportions and not because of the spectral response. In the negative part are soils 2RU, 7LVd, 8LVd, and 10CX, separated by the proportions of clay and Al_2O_3, which interfere to reduce the spectral response.

PC2 (Figure 5) is responsible for the separation of soils because of its level of development. In the positive quadrant are samples 9RL and 10CX, which are younger soils (eluvial) and have high contents of silt, sand, and Fe_2O_3, which constitute the primary minerals present in the soil. In the negative part are the more developed soils, such as 6NVd and 8LVd, which are composed of high levels of clay.

In the PC3 (Figure 5) positive quadrant, soil 7LVd is separated due to the higher Fe_2O_3 and the relatively high TiO_2 contents. In the negative part is soil 4LVd due to the higher content of OM.

PC4 and PC5 do not have a significant participation in the model to characterize the spectral response.

The Principal Components Analysis (PCA) validated the laboratory spectroscopic methods, allowing the grouping or separation of the spectra and variables that present higher interference in the spectral response. It was observed that the PCA permitted the identification of different levels of development of the soils (young and mature soils).

OM and Fe stayed in separated quadrants, possibly because the highest participation of iron is in the hematite form.

The Principal Components Analysis (PCA) was also used to evaluate the potential of the CCD sensor regarding the study of soil spectral response.

The second matrix used in this study is composed of 10 samples and 12 variables, with the spectral data of the CCD sensor bands (CCD1, CCD2, CCD3, and CCD4) of the CBERS-2b Satellite and the physical-chemical data (sand, silt, clay, OM, Al_2O_3, Fe_2O_3, SiO_2, and TiO_2). Data treatment revealed 9 PCs (Table 4) for a total of 100% of the accumulated variance. From this set, 5

PCs were separated, which account for 98.26% of the variance, for the evaluation of the set of data.

Table 4 – Principal components (PCA) and percentage participation in the evaluation of the band data.

PC	% of PC	% of accumulated variance
1	54.42	54.42
2	16.67	71.09
3	10.16	81.25
4	9.39	90.64
5	7.06	97.70
6	1.18	98.88
7	0.75	99.63
8	0.25	99.88
9	0.12	100.00

Figure 6 shows that PC1 (54.42 %) contains the following samples in the positive quadrant: 1LVd, 2RU, 6NVd, 7LVd, and 8LVd. The variable bands CCD1, CCD2, CCD3, and CCD4, clay content, and Al_2O_3, Fe_2O_3, SiO_2, and TiO_2 contribute to enclose these samples. Clay attenuates the spectral response; however, the CCD sensor did not identify the clay interference in the spectral response.

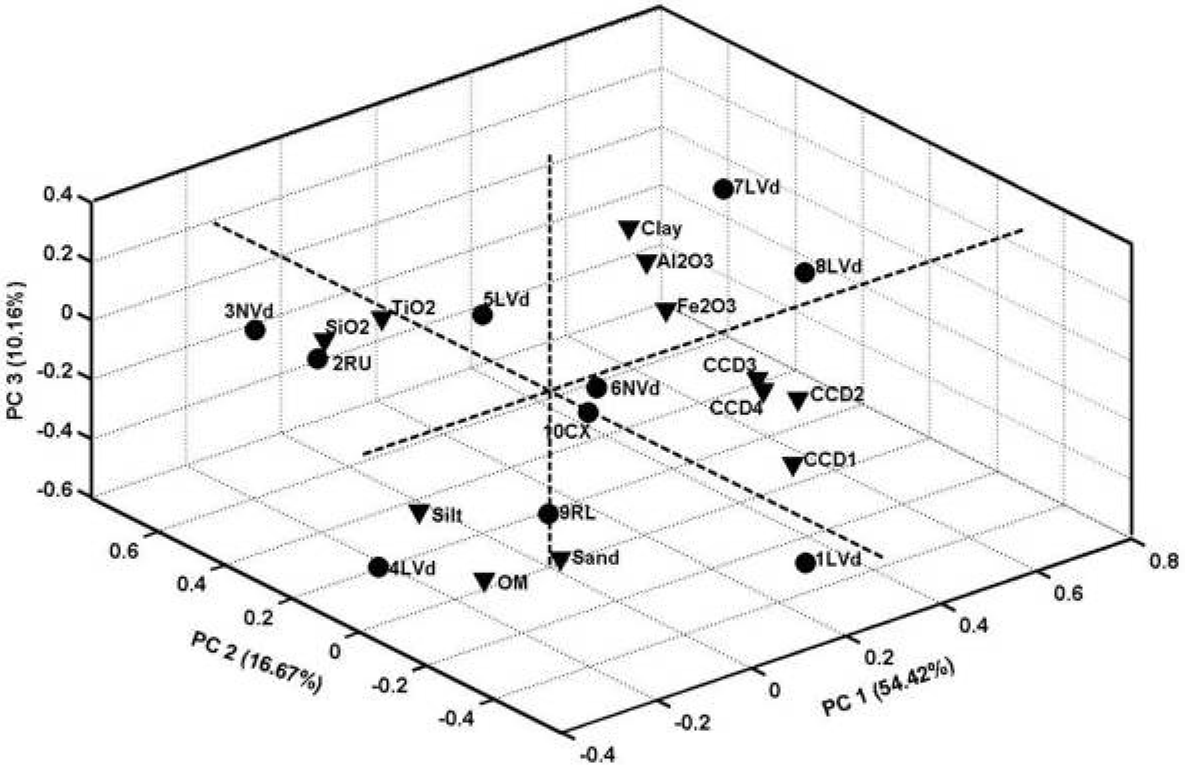

Figure 6 – Scatterplot of Principal Components (PC1 x PC2 x PC3) of the bands.

Samples 3NVd, 4LVd, and 9RL are in the PC1 negative part (Figure 6). OM has a higher influence upon sample 4LVd and the sand content in the 9RL sample. Samples 2RU and 3NVd are separated due to the silt content.

In contrast to the spectra PCA, the bands did not enclose the soil samples with the variables that intensify the spectral response. The variables clay and aluminum oxide, which attenuate the spectral response, are found together with the bands in the positive quadrant, separating samples 7LVd and 8LVd, which show high spectral responses in the spectra obtained in laboratory. Samples 4LVd and 9RL, which show the highest OM contents, are correlated to the spectral response.

The spectral responses obtained from the CCD sensor separate, in the negative part, samples 4LVd, 9RL, and 10CX due to the OM content, demonstrating that, in the current conditions, the CBERS-2-CCD (stage of development and improvements) shows promise for studies concerning soil spectral response.

In evaluating the spectral behavior (Figure 6) of the samples measured by the CBERS 2 bands (variables CCD1 to CCD4), it is important to mention that the data obtained represent a response of the target (sample site) in an intact manner, in other words, with the remains from cultivation, weeds, and even the possibility of a crop in an early vegetative cycle. All these data contribute to the average spectral response of each pixel. The variables for the spectra obtained in the laboratory, such as ECCD1 to ECCD4, arise from a sample from the respective sampling site, for which the material was homogenized and dried, with no presence of remains from cultivation.

The data from the PCs shown in Figures 5 and 6 demonstrate the good potential for developing soil studies using spectroscopic data. Of the variables used for studying the soil data, the ones contributing the most for separating or clustering soil samples were OM, textural data, and levels of iron and of TiO_2.

Conclusions

The physical-chemical data, when analyzed by the described method, showed that the spectral response of OM, kaolinite, gibbsite, iron oxides, and texture (silt, sand and clay) give the greatest interference. The data on aluminum oxide and for silicates are also important, but these are already included in the texture aspects.

The use of Principal Components Analysis to evaluate 12 variables, including the chemical, physical-chemical, and laboratory spectroscopy data as well as the spectral data from the CBERS-2b satellite, demonstrate that this method is adequate in the evaluation of soil samples since it clusters or separates samples, grouping those with the same characteristics.

The use of images from the CCD sensor, while presenting limitations due to interference between the satellite and the soil (cultivation remains, weeds, projection angle for slopes and relief), revealed good potential for studying the spectral behavior of soil. It is recommended that, in future studies, the sampling sites are enlarged and prepared in advance, leaving 50% intact and 50% plowed and leveled. The plowed soil portion would be free from interferences (cultivation remains, weeds). The reflectance data from the intact and plowed portions could generate an adequate correction factor for extrapolating the study to larger environments which display the same conditions as the intact sampling sites. Another aspect is the need to control surface radiation, soil humidity, and the optical thickness of the atmosphere and, subsequently, to collect samples on the date and time of the soil imaging by the satellite. A portable radiospectrometer can also be used to collect spectral data in the field under natural conditions, and it can then be used in the laboratory to repeat the measurements in a controlled environment.

Although this investigation is not conclusive, it is a contribution to the study of tropical and sub-tropical soils by fast and inexpensive methods, which can yield a great deal of information about the spectral responses of soils in larger areas in the country.

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