

Estimation of Soil Properties by Orbital and Laboratory Reflectance Means and its Relation with Soil Classification

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Abstract: Wet chemistry methods to extract soil properties such as Fe₂O₃, TiO₂, MnO and clay are cost effective, time consuming and environmental polluter. Moreover, a large set of samples has to be collected for precise spatial mapping. Ordinary surface soil mapping is a problematic method. Accordingly, non destructive technologies, such as remote sensing methods can provide important vantages. The objective of the present work was to estimate soil attributes by laboratory and orbital sensors and compare these results with soil classification. The study area is a 473 ha bare soil field located in the region of Barra Bonita, Brazil. A sampling grid of 100 by 100 m was established and the exact position of each point was georeferenced, and sent to traditional (wet) laboratory analyses. The soil samples reflectance were also acquired by a laboratory sensor using artificial illumination (450 to 2500 nm). Over the same selected ground area reflectance data were extracted from the TM-Landsat-5 image. Prediction equations between the satellite and laboratory reflectance data and the wet chemistry were generated for each attribute. Most of the generated equations presented high and significant R² such as for the Fe₂O₃ with 0.82 for laboratory and 0.67 for the orbital reflectance data. The comparison between reflectance estimates and laboratory wet measurements for iron presented 92.2% success for the laboratory and 91.3% for the orbital sensors. The comparison for the texture intervals, showed 65% and 50% success for laboratory and orbital data respectively. The iron contents obtained by the sensors allowed to better remotely classify soil classes. Soil extractions to determine these attributes can be substitute by spectral reflectance models based on the present methodology.

Keywords: Quantification, reflectance, soil attributes, laboratory sensor, radiometry.

INTRODUCTION

Quantitative assessment of soil attributes by remote sensing means represents a challenge to researchers in the areas of both remote sensing and soil science. Various analytical approaches to achieve this objective have been suggested, developed and examined over the years in order to establish a practical and acceptable approach. One of the powerful known method is the Near-Infrared Analysis (NIRA) approach which looks for the best model to derive chemical data from spectral information mostly in the near infrared region (1,100-2,500 nm) and under laboratory conditions. This method employs a statistical based analysis to determine the best spectral model in which soil chemical composition can be estimated solely from the spectral properties of the sample [1]. This methodology was first implemented 30 years ago for the rapid analysis of grain moisture [2] and today it is well recognized and widely accepted in many disciplines and applications. The beginning of infrared studies dates back to the fifties, with advances being made and interest increasing in the sixties, motivated by the need for application in agriculture. Spectral evaluation methods were found to be more practical and faster than traditional techniques used in agriculture. In recent years, the remote

acquisition of spectral information of terrestrial surfaces increased dramatically. Where significant growing of air and space born systems from one hand and significant accumulation of knowledge about the soil reflectance spectroscopy from the other have stimulated this process. Also new development and massive marketing of field spectrometer exposed this technology to many new users, never before considered its utilization.

Today, NIRA methods are well accepted and applied in different areas [3]. NIRA permits the analysis of various soil constituents at the same time [4]. In addition to NIRA, Sorensen and Dalsgaard [5] and Brown [6] used visible to infrared light for the soil constituents determination and obtained good results for the quantification of organic matter, clay and iron. Lagacherie [7] and Galvão [8] show that even the "spectral featureless" VIS-NIR spectral region can be used to determine several soil constituents. The NIRA methodology is based on multiple linear equations which are constantly calibrated according to the region studied and to the portion of the electromagnetic spectrum available.

The spectral features of soil constituents in the visible and short-wave infrared range (450-2,500 nm) are associated with electronic transition (mostly in the VIS region) and molecular vibration (mostly in the SWIR region) of specific chemical groups. The obtained features are used to select the precise spectral ranges (or bands) for the NIRA analysis [9, 10]. Soil minerals present distinct "spectral fingerprints" in this SWIR spectral regions as a result of specific or com-

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bined absorption bands such as those of OH⁻ and CO₃ groups [11] whereas the VIS-NIR region associated more with electronic transition of Fe bearing minerals and organic matter compounds. In general, the spectral quantitative approach NIRA, is based upon the assumption that the concentration of a given constituent is a linear combination of various absorption features presented across the spectrum. This approach is empirical, and no physical or chemical assumptions are needed. Nevertheless in order to minimize over fitting of noise, each selected model has to lean on significant spectral feature assignments.

A comprehensive review of the NIRA approach in soil science can be found in both Mulley [12], Viscarra Rossel [13] demonstrating a growing interest of this technology by many workers.

The spectral reflectance of a given surface is extremely complex, and is affected by the number and type of the present constituents, their concentration, particle size, number, weight, geometry and measured methodology [14]. As the NIRA methods are based on the measurement of small changes in the absorbance reading that occur at multiple wavelengths it is important to minimize some of the above factors in order to assess quantitatively the constituent in question.

All soil attributes are important, but with different percentage of contribution for agriculture. Some attributes may be more directly related to a part of agricultural planning whereas others might be important to soil classification or general mapping. For example, phosphorus represents an essential element in plant development and, consequently, its content plays an important role in fertilizing recommendations (planning of chemical management in a given area). On the other hand, there are elements, such as Fe₂O₃ that are related to soil classification and that plays an important role to pedologists. According to Embrapa [15], information about the content of iron oxide, helps in the classification of large soil groups and families (soil surveys as a basis for planning) [15]. The type and relative quantity of iron oxides has a direct effect on the yellow and red color of soils. Yellow soils predominantly present a high content of goethite, which is responsible for the greater absorption of phosphorus per weight unit when compared to red soils with similar quantities of hematite [16, 17]. In a way, soil color is indicative as to whether the soil can retain more or less phosphorus. However, the quantity of free iron is more important in soil classification since it helps to evaluate the various iron groups and characterize the soil forming conditions [15]. Since obtaining free iron content from soils is expensive, time consuming, and polluted, number of ground samples sent to the laboratories are rather limited and consequently render precise soil surveys.

It is therefore very helpful if approach such as the NIRA method will be implemented into the soil matrix analysis to determine constituents difficult to assess as the former example. Some authors have demonstrated significant correlations between spectral reflectance and total Al₂O₃, MgO and Fe₂O₃ content under laboratory conditions using large number of spectral bands (Table 1). Simulating orbital data, Ben-Dor and Banin [9] were able to show that re-sampling of the spectral number to the six TM channels enabled the detection of soil constituents such as CaCO₃, SSA, SiO₂ and LOI.

However, the question remains as to whether it is possible to quantify soil properties under real orbital conditions using sensors mounted on satellite at 800 km above the earth. If the answer is positive, then the next step is to check whether this technique can be applied to soil mapping activity. Coleman [25] obtained very low coefficients with this approach trying to map Fe₂O₃ but emphasize the need for further studies on this element in order to improve and ratify the technique, increasing its reliability in terms of practical applicability.

Table 1. Review of the Correlations Found in the Literature Between Spectral Reflectance and Total Al₂O₃, MgO and Fe₂O₃ Content

Authors	Soil Attribute	R ²
Chang (2001) [18]	MgO	0.68
Shepherd and Walsh (2002) [19]	MgO	0.81
Cozzolino and Moron (2003) [20]	MgO	0.90
Islan (2003) [21]	MgO	0.63
Chang (2001) [18]	Fe ₂ O ₃	0.64
Cozzolino and Moron (2003) [19]	Fe ₂ O ₃	0.90
Islan (2003) [21]	Fe ₂ O ₃	0.52
Brown <i>et al</i> (2006) [6]	Fe ₂ O ₃	0.77
Galvão (2001) [22]	Al ₂ O ₃	0.68
Dunn (2002) [23]	Al ₂ O ₃	0.79
Cohen (2005) [24]	Al ₂ O ₃	0.91

A recent review of spectral analysis of soils from hyper spectral technology is summarized by Ben-Dor [26] showing a promising capability to use remote sensing for many soil applications. The advent of hyperspectral sensors, such as the Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS), has permitted the quantification of soil attributes, such as Al₂O₃ [22, 27]. Other hyperspectral sensors such as the DAIS-7915 also demonstrated a capability to quantify several important soil properties as organic matter, electrical conductivity and moisture [1]. Ben-Dor [28] have shown that the free iron oxides content in sand dunes areas can be assessed on a pixel by pixel basis using CASI hyper spectral sensor. Using ROSIS airborne imaging sensor, Bartholomeus [29] have verified capability to assess soil iron oxide content on partially vegetated areas. Recently, Richter [30] have demonstrated a way to assess for soil degradation on semi arid environment using free iron content applying the spectral model on HyMAP airborne hyperspectral scanner data.

Based on these considerations, the objective of the present study was to examine the capability of the NIRA approach to analyze Fe₂O₃, Al₂O₃, Al₂O₃/Fe₂O₃, SiO₂, TiO₂, Ki, Kr and clay content in Brazilian soils using multi spectral satellite sensors and to examine the feasibility of the extracted spectral model on soil classification.

MATERIALS AND METHODS

Characterization of the Study Area

The area of 473 ha selected for this study is located in the southeast region of São Paulo state, Brazil. The altitudes

ranging from 520 to 710 m above sea level. The climate of the region was classified according to the Köppen system as a Cwa type, i.e., a mesothermic climate [31]. The lithology is mainly represented by the occurrence of a set of basaltic rocks intercalated with sandstone. In addition, the other formation of a group was observed, which is characterized by sandstone with clayey cement, shale and conglomerates, with a predominance of sandstone [32].

Soil Sampling and Analyses

A grid with 100 x 100 m (about 3X3 pixel size of TM sensor) was established where points were marked with numbered stakes, with a total of 473 georeferenced (Submetric GPS) stakes. In each point we collected soil samples at two depths, 0-20 cm (expressed as layer A) and 80-100 cm (under surface layer B), with a bore-hole collector. For each sample, the soil color was determined in wet condition using a Minolta CR300 equipped with a Munsell color chip. Samples were submitted to chemical [33], granulometric and sulfuric acid digestion [34]. The following parameters were thus obtained: Total aluminum (expressed as oxide Al_2O_3), total free-iron (expressed as oxide Fe_2O_3), Al_2O_3/Fe_2O_3 ratio, silica (expressed as oxide (SiO_2)), and titanium (expressed as oxides TiO_2), index of the weathering stage ($K_i = SiO_2/Al_2O_3$) and index of the weathering stage for well-drained medium texture soils ($K_r = SiO_2/Fe_2O_3 + Al_2O_3$).

Spectral Data Collection

(a) Laboratory Spectral Acquisition: Data were obtained with the Infra-Red Intelligent Spectroradiometer (IRIS) sensor [35], which covers the spectral range from 450 to 2,500 nm. Soil samples from soil layers A and B were dried at 45°C for 24 h, ground and sieved to < 2-mm. The samples were then placed on petri dishes and illuminated with a 650-W halogen lamp. The electric current feeding the lamp was stabilized with a 1% power source. A white plate (Spectralon Reflectance) was used as standard [36]. The lamp was situated at 61 cm from the soil sample and the distance between the sample and the sensor was 27 cm, with the lamp inclined 20° at nadir [16]. The data were then analyzed with the Convis software for regularizing and filtering the reference plate data [37]. The relationship between the energy reflected by the soil sample and the energy reflected by the reference plate provided the Bidirectional Reflectance Factor (BRF).

(b) Satellite Spectral Data Acquisition: The Landsat-5 TM sensor was used for this stage, using, band 1, 2, 3, 4, 5 and 7. The digital number were converted to radiance using the gain and offset parameters provided by EOSAT and then transformed into reflectance data using the 5S model (Satellite Signal Simulation within the Solar Spectrum) [38, 39]. The sampling points of the grid were superimposed on the geocorrected satellite images. Geometric correction was necessary to adequately position the image within the real field. For that purpose, planialtimetric maps (scale 1:10,000) obtained from the Regional Action Coordination Office (São Paulo State) were used. In addition, points obtained in the field with the Global Positioning System (GPS) with a submetric error were used. In order to maintain the pixel reflectance value as close as possible to its original value, a nearest neighbor interpolation process, method, was used, correcting only scale distortions, displacement or rotation between the

image and the terrestrial projection [40]. The reflectance value of each pixel was then collected.

Statistical Analysis and Comparison of the Results

The NIRA model was performed with 50% of the data, as the validation was made with the other 50%. The points used to generate the models were chosen randomly and were representative of the entire study area. It was performed two statistical models, as for laboratory and satellite measurements.

Statistics with Laboratory Spectral Data: Spectral data acquired in the laboratory with the IRIS system permit a higher radiometric and spectral resolution. The selected bands for the development of the models were based on Nanni and Dematté [41] findings. The authors based their method on the necessity to choose selected bands to input the statistical model. Three concepts were used to select the bands from laboratory spectral curves: 1) empirical observation of the analyzed spectrum, which showed spectral reflectance curve inflections, convex and concave portions; the variation of reflectance intensity in all spectrum; 2) literature observations to depict the correct wavelengths that have relation with soil attributes [42, 43], and 3) wavelengths characterized by a strong inflection, such as iron oxides (481 nm), water and OH groups (1,417 and 1,927 nm), kaolinite (2,206 nm) and gibbsite (2,265 nm).

Based on these observations twenty two “bands” in specific wavelength (or range of wavelength) were chosen. When the band is specific, e.g. 480 nm, the reflectance data is exactly from this wavelength. If the band is a wavelength-range, e.g. 480-580, we used the mean spectral reflectance that composed this range. On the other hand, some parts of the spectrum had an evident inflexion (absorption feature), confirmed by the consulted literature. In these cases we made a specific methodology, expressed as “Reflectance Inflexion Difference, (RID)” values. The RID value is the difference between reflectance factor at the highest and lowest point of inflection (or amplitude of spectral data at this range), represented by one unique data. In this case, 13 RID values were selected (demonstrating height curve between peak and valley). Thus there were in total 35 independent variables.

Multiple linear regression equations for laboratory radiometric data were established for each soil attribute, thus using the 35 independent variables of the GER sensor. Fifty percent of our surface samples were used to develop the model whereas the other 50% (unknown samples) were used to validate the procedure.

The following soil attributes (dependent variables) were correlated with spectral characteristics obtained in the laboratory: aluminum oxide (Al_2O_3), iron oxide (Fe_2O_3), Al_2O_3/Fe_2O_3 ratio, silica oxide (SiO_2), titanium oxide (TiO_2), index of the weathering stage ($K_i = SiO_2/Al_2O_3$), index of the weathering stage for well-drained medium texture soil ($K_r = SiO_2/Fe_2O_3 + Al_2O_3$), and granulometry (Sand, silt and clay).

Statistics with Satellite Spectral Data: Multiple linear regression equations for orbital radiometric data were established for each soil attribute, thus using the six bands of TM sensor as independent variable for 50% of our surface sam-

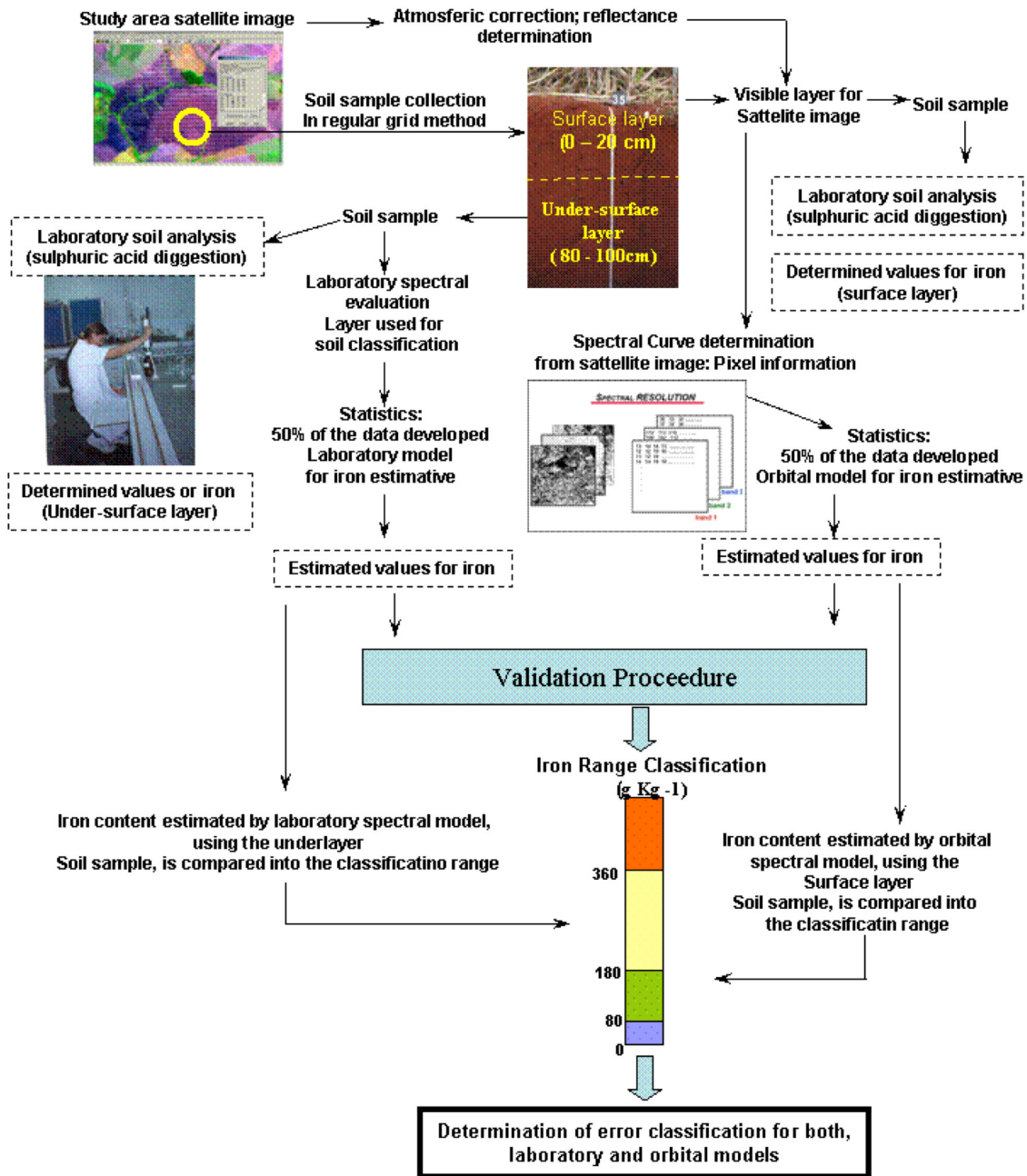


Fig. (1). Flowchart of the methodology.

ples (layer A). The other 50% unknown samples were used to validate the procedure.

Validation stage - Relationship between spectral data (laboratory and satellite) with soil iron classification: Each soil sample analyses was classified into the following categories, (according to [15]): hypoferric (low Fe_2O_3 content, < 80 $g\ kg^{-1}$), mesoferric (medium Fe_2O_3 content, 80 to < 180 $g\ kg^{-1}$), ferric (high Fe_2O_3 content, 180 to < 360 $g\ kg^{-1}$), and perferric (very high Fe_2O_3 content, $\geq 360\ g\ kg^{-1}$) [14].

The models developed for laboratory spectral data for Fe_2O_3 were used to determine the estimated value for each sample. Thus we could compare when the iron classification was done by the interpretation of the determined method (laboratory traditional analyses) and by the estimated spec-

tral model. Our point here was to compare the iron classification capability as it was characterized by a varying irons range. For example, we had a soil sample analyses with 300 $g\ kg^{-1}$ and is classified in ferric. The spectral data of this sample goes in-through the model for iron estimate, and generate a 330 $g\ kg^{-1}$. In this case, the value allows us to classify the iron as ferric. As the Determined and the Estimated was classified equal, the sample interpretation is correct.

The same method was used to validate clay contents, based on clay classification, as following: sandy ($\leq 150\ g\ kg^{-1}$ clay), medium 1 (151 to 250 $g\ kg^{-1}$ clay) and medium 2 (251 to 350 $g\ kg^{-1}$ clay) [15]. Fig. (1) presents a flowchart of the methodology.

Soil Attributes Maps

Soil iron classification is based upon the under-surface soil sample. The laboratory spectral model was also used to estimate iron contents from under-surface. Thus, we obtained spectral data information for the under-surface layer (80-100 cm) of each soil sample in the grid. These spectral data was inserted into the models and the iron value was used to classify iron. With this we generated an iron distribution map that was based on the laboratory sensor.

The same procedure was applied to the surface layer (A) using both laboratory and TM data that enabled the iron classification of each pixel grid. With this we generated an iron distribution map that was based on the both TM and laboratory sensor.

Using the wet chemistry data and interpolation techniques we generated a ground truth soil map that was used as a reference to compare the iron classification results of both, laboratory and satellite sensors.

RESULTS AND DISCUSSION

Quantitative Analysis of the Soils Spectral Laboratory Data

The laboratory equations based on the 35 independent variables (22 bands and 13 RID) for the sulfuric acid digestion samples are shown in Table 2. The Al_2O_3 equation consisted of largest number of significant variables (nine). The equation with the smallest number of significant variables (4 variables) was for the SiO_2 , while the equation for Fe_2O_3 contained 5 variables. Thus, statistical analysis permitted the selection of the most representative bands and RID for each soil attribute. Multiple analysis techniques permitted the definition of bands and RID that best characterized each attribute, in agreement with Huete and Escadafal [44], Demattê and Garcia [42] and Nanni [45] findings. Al_2O_3 , Al_2O_3/Fe_2O_3 , Fe_2O_3 and TiO_2 showed high determination coefficients ($R^2 > 0.8$) (Table 2, $n=206$, significant level at

1%) with these values being higher than those obtained by Demattê and Garcia [42] for Fe_2O_3 ($R^2 = 0.64$, $n=12$, significant level at 1%). These significant coefficients are in agreement with Ben-Dor and Banin [9] and Nanni and Demattê [41].

The 0.67 determination coefficient obtained for Kr was also considered significant. The lowest R^2 of 0.43 was observed for Ki, where its equation was reliable (Table 2). Significant determination coefficients for Ki ($R^2 = 0.69$) were obtained by Demattê and Garcia [42] when studying soils derived from basalt, which a relationship was established between the weathering stage and spectral reflectance. Weathering indexes are determined by equations and susceptible to variation, different from the other parameters. The estimation of clay content showed significant with high determination coefficient (> 0.8) (Table 2), in agreement with Nanni and Demattê [41] who obtained a 0.91 R^2 . Comparing Coleman [46] consideration that a determination coefficient of 0.68 is high for clay, our results are quite expressive. The high coefficients of determinations obtained in studies published later indicate the importance of employing a significant number of bands in the models. In agreement with Demattê and Garcia [42] and Ben-Dor [1], care should also be taken to avoid effects of noise over-fitting in the models by means of previous statistical tests.

These results obtained in laboratory for clay and Fe_2O_3 have been confirmed by Nanni and Demattê [47]. These authors tested pre-established models obtained from a different region on the quantification of Fe_2O_3 . It can be concluded that in general, the results were positive, indicating that the models used estimated significantly the Fe_2O_3 content in the soil. Variations in the R^2 are due to a series of factors, such as soil variability, representative of the samples, number and specificity of the selected bands, acquisition geometry, equipment stability, among other factors. The spectral behavior of soil samples is known to vary according to the soil depth in question, basically as a result of organic matter [48,

Table 2. Multiple Equation Using 22 Bands and 13 RID Acquired by Laboratory Sensor

Atributte ^a	Multiple Equation ^b	R ^{2*}
Clay	$376,23728+(4092,67466*H3)+(10972*H7)+(1409,95843*H2)+(-25070*B11)+(23006*B16)+(-23085*H11)+(-30702*B10)+(-19095*B17)+(8651,36527*H12)+(-2273,14097*H1)+(-4697,25743*B15)+(-6041,71261*B8)$	0,8570
Al_2O_3	$92,36208 + (1213,86097*H3) + (-7576,03710*H11) + (2610,00589*H10) + (3890,10521*H12) + (1619,05064*H7) + (3342,92742*B7) + (-2264,96298*B11) + (-888,77054*H8) + (-1251,32151*B6)$	0,8728
Al_Fe ^c	$1,29518 + (-13,66498*H2) + (21,74558*B1) + (-9,07322*H4) + (25,97556*H10) + (46,14417*H12)$	0,8835
Fe_2O_3 ^d	$110,81409 + (-9368,27072*H11) + (757,29756*H2) + (-3338,68863*H13) + (9490,32024*H12) + (-1005,39436*H8)$	0,8254
Ki ^e	$1,59767 + (-20,91352*H4) + (11,99758*H8) + (7,42979*B18) + (-25,59849*B2) + (9,96940*B10) + (-12,12550*H2)$	0,4259
Kr ^f	$0,88979 + (21,01051*H8) + (50,16260*H11) + (27,06973*H1) + (-29,90358*H5) + (-33,11525*H12) + (-1,40514*B19)$	0,6787
SiO_2 ^g	$126,44349 + (1547,67871*H3) + (278,76155*H2) + (342,13833*B12) + (-837,78410*B21)$	0,7205
TiO_2 ^h	$35,82973 + (-541,11648*H11) + (345,09118*H3) + (-505,30168*B21) + (229,06336*B12) + (-855,81924*H13) + (-199,65289*B3) + (400,56645*B8)$	0,8751

^aNumber of observation: Clay, 473; other attributes, 206; ^bB1...B22; H1...H13, bandas e alturas selecionadas; ^cSignificance at 0,01 %;

^dRelation $Al_2O_3 + Fe_2O_3$; ^eFree iron (total iron obtained by sulfuric acid digestion); ^f Weathering index obtained by: $SiO_2/Al_2O_3 + Fe_2O_3$.

^g Weathering index obtained by: $SiO_2/(Al_2O_3 + Fe_2O_3)$; ^h Silicium oxide; ⁱ Titanium oxide.

B stands for Bands (selected bands).

H stands for Hights (Spectral inlflectance difference data) = explained in the methodology.

49]. Therefore, the question can be raised as to whether "models should be elaborated using separate samples from the surface and under-surface layer or not".

In the first studies [46], soil samples from the surface layer were used to elaborating the models. Nanni [45] established separate spectral models for the surface and under-surface layer and obtained significant coefficients of correlation for the soil properties examined. This author then validated the models obtained for the surface layer using unknown samples from the under-surface layer and vice-versa, obtaining also significant coefficients of correlation. However, in the present study, although the samples were not separated (surface and under-surface), for generating the models or validating the equations, high coefficients were also obtained (Table 2). These results indicate that it is not necessary to elaborate independent models for each soil depth, as this procedure is practically too complicated and does not provide better accuracy. However, it should be noted that the samples selecting for the model indeed representing the entire study area in question.

Quantification of Soils by Spectral Orbital Data

In this stage we used the 6 TM bands in the VIS-NIR-SWIR region to allocate a reliable model for the soil attributes. Except for the quantification of Al₂O₃/Fe₂O₃ ratio, the TM band 7 was selected in all spectral models (Table 3). The TM band 4 presents in 5 of 8 spectral models and always together with TM band 7. Nanni [45] showed the presence of the TM band 7 for SiO₂, Fe₂O₃ and TiO₂, whereas TM band 4 was not selected, in contrast to the present results. Coleman [25] also observed the presence of the TM bands 7 and 4 for Fe₂O₃. The selection of the TM band 7 might be associated with the influence of younger, more clayey soils with a Ki > 2, a fact that leads to higher water retention and, together with kaolinite, to a higher absorption of the TM band 7 which was presented in all spectral models of the attributes studied (Table 3). However, the participation or not of a given band is directly related to the specific soil characteristics of a region, which probably explains the differences between the studies results. The highest coefficient of determination (0.72) was observed for TiO₂ (Table 3), in agreement with the results reported by Nanni [45] and confirmed by Ben-Dor and Banin [9] and Nanni and Demattê [41]. Coefficients of determination with 0.67 and 0.65 were ob-

tained for Al₂O₃, Fe₂O₃ and SiO₂, respectively. The coefficient obtained for Fe₂O₃ (0.67), was slightly lower than those obtained by Nanni and Demattê [41], (R² of 0.72) but much higher than that reported by Coleman [25] (R² of 0.288). The significant values for Ki, indicate its relationship with soils weathering and it is in agreement with Demattê and Garcia [42].

Coleman [25], in their paper entitled "Is it possible to quantify soil attributes through sensors installed on spatial platforms?", reported significant R² values ranging from 0.1 to 0.4 for sand, silt, clay, iron and organic matter. In another study, Ben-Dor and Banin [9] showed that convolved TM spectra of soil can be used to predict CaCO₃, SiO₂, LOI (lost on ignition) and SSA (specific surface area) with R² ranging from 0.46 to 0.71 in the validation stage. We can reaffirm this possibility since the determination coefficients in the present study were also significant (Table 3). The variation in the significance of the models observed among studies reported in the literature are again intimately related to the methodology and to the soil population used, especially in the case of orbital data evaluation. In reality, soil data extracted by a satellite positioned at a 800 km distance are influenced by a large number of interfering factors such as geometric and atmospheric variations, mixed pixel problem, adjacency effect, surface roughness, BRDF effect, surface residues, presence of vegetation, atmosphere attenuation, soil crust status and the sensors electro optics variation, among others [50]. Nevertheless, many of these factors can be minimized by different methods, such as atmospheric correction, high sun elevation, flat terrain and the choose pixel with bare soil, as reported by Demattê and Nanni [43].

Iron Content Estimated with Laboratory and Satellite Sensors and its Relationship with Soil Classification

The importance of the reliability degree in the estimation of a given soil attribute is intimately related to the objectives of this quantification. A soil attribute such as phosphorous for example, can be estimated and assessed in terms of its absolute value, for later concentration calculation. On the other hand, this same phosphorous absolute value can be only classified as low, medium or as high content.

According to the current soil classification [15], iron content is important for the discrimination of important soil

Table 3. Multiple Equation Using 6 Bands of the TM Landsat Sensor

Atributte ^a	Multiple Equation ^b	R ² *
Clay	699,99540+(-13,44352*TM7)+(-12,69294*TM5)+(13,03814*TM2)	0,6140
Al ₂ O ₃	189,27590 + (2,91733*TM_3) + (-3,97853*TM_4) + (-6,95007*TM_7)	0,6783
Al_Fe ^c	-0,27048 + (-0,27805*TM_1) + (0,10476*TM_5)	0,4799
Fe ₂ O ₃ ^d	290,71175 + (12,04310*TM_1) + (-5,54129*TM_4) + (-10,24985*TM_7)	0,6724
Ki ^e	1,13241 + (0,05412*TM_4) + (-0,05408*TM_5) + (0,08867*TM_7)	0,3169
Kr ^f	0,17683 + (-0,11305*TM_1) + (0,03486*TM_4) + (0,04700*TM_7)	0,5390
SiO ₂ ^g	189,49259 + (-3,18311*TM_4) + (-4,94352*TM_7)	0,6531
TiO ₂ ^h	76,88838 + (2,71784*TM_1) + (-1,54095*TM_5) + (-1,34536*TM_7)	0,7210

^aNumber of observation: Clay,236; other attributes, 103; ^b TM1...TM7, bands of sensor TM of Landsat satellite; *Significance at 0,01 %; ^cRelation Al2O3 + Fe2O3; ^dFree iron (total iron obtained by sulfuric acid digestion); ^eWeathering index obtained by: SiO₂/Al₂O₃; ^fWeathering index obtained by: SiO₂/(Al₂O₃ + Fe₂O₃); ^gSilicium oxide; ^hTitanium oxide.

classes. The iron content of each sample obtained by laboratory traditional means was then classified into the following ranges: hypoferric, mesoferric and ferric classes. Thus, spectral model constructed using laboratory (and satellite) sensor, was used to determine iron content of each soil sample. This absolute value was compared to see in which iron classification it would better fit, and thus compare with the same pro-

cedure using iron content obtained by the laboratory analysis (Table 4). The data obtained by the sensor in the laboratory refer to the under-surface layer (B), which is used for the real soil classification procedure (Fig. 2b, c). Likewise, spectral model constructed with the TM satellite sensor readings, was used to determine the iron contents of the top- surface soil layer (A) (Fig. 2a).

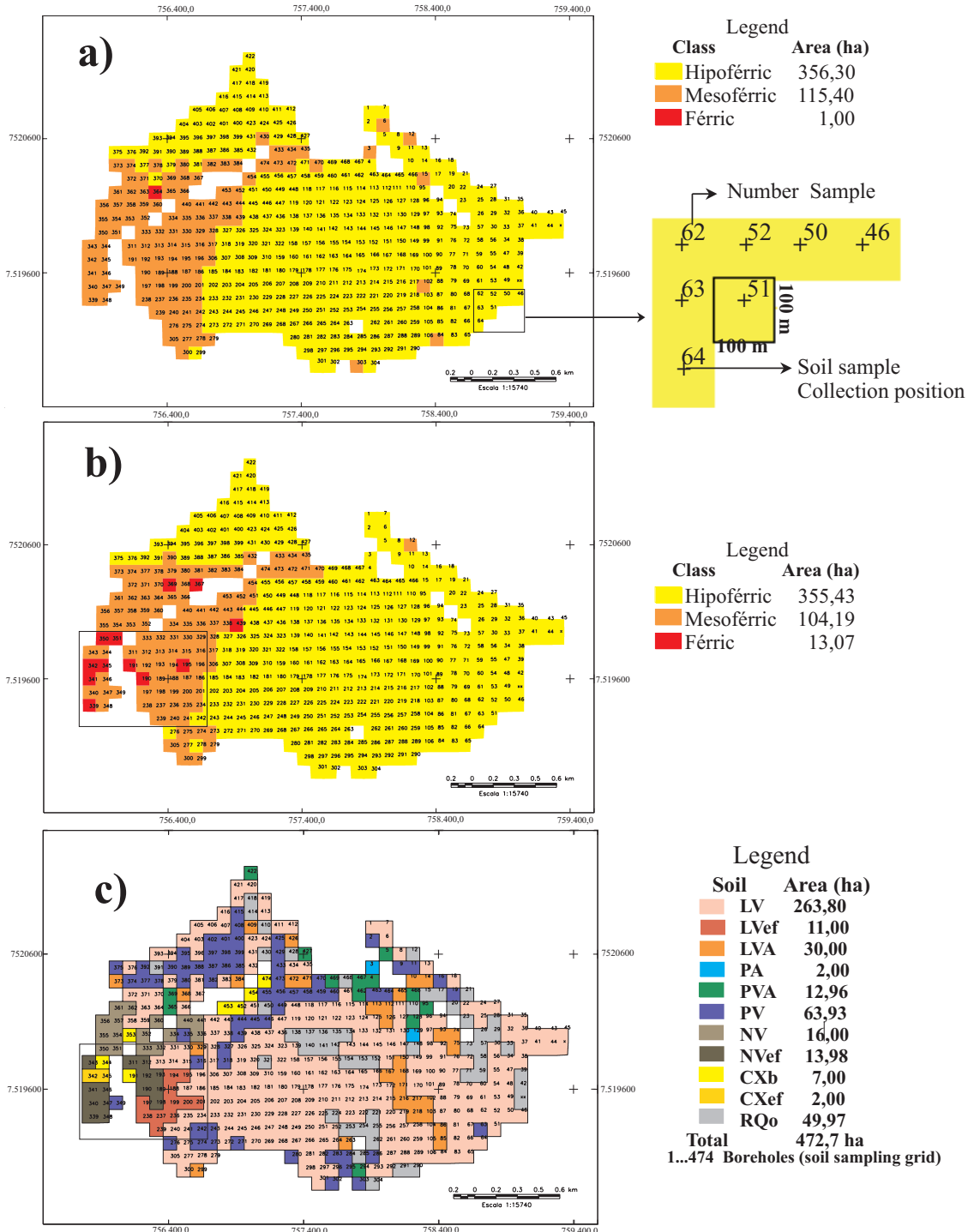


Fig. (2). (a) Map of iron classification (according to Brazilian Soil Classification) determined by estimated iron contents of orbital data (surface soil layer). (b) Map of iron classification estimated by IRIS sensor results (undersurface layer); (c) Detailed Soil Map.

Iron content estimated by laboratory spectral model matched in hypoferric class in 96.3%, and 100% in mesoferric class (Table 4). The ferric class of iron was the one that presented high error, 71.4%. The data matrix indicate a higher incidence of hypoferric (82 samples) and mesoferric (14 samples) soil samples against the ferric one (7 samples). The more representation of the described classes performed a more robust laboratory spectral model, thus interfere in the results. Also, the “confusion” of these samples might have been due to the proximity of the iron limits between the mesoferric and ferric class. We found that 72% of the samples analyzed presented absolute iron values of up to 200 g kg⁻¹, i.e., only 20 g kg⁻¹ above the limit between the mesoferric and ferric level which was 180 g kg⁻¹.

Spectral model constructed using satellite sensor, presented low error on the validation procedure (Table 4). From the 84 soil samples classified as hypoferric (using laboratory traditional analyses), 80 were correctly classified using the spectral model, thus reaching 95.2 % correct. The mesoferric iron classification performed 0% error. Only 4 samples were confused, i.e., they should have been classified as hypoferric while the estimated values considered them to be mesoferric. Again, this “confusion” might be associated with the proximity of the iron content limits between one class and another. The ferric class is classified as < 80 g kg⁻¹ and the hypoferric class from 80 to 180 g kg⁻¹. Another important factor is the pixel size of the satellite image, in this case 30 x 30 m, where the collected reflectance value represents the response of interaction between elements within the pixel [1]. Despite the pixel considerations, we had 100 % correct classification to mesoferric iron class. In contrast, the 5 samples classified as ferric were classified as mesoferric (Table 4).

The same confounding effect on the more saturated iron classes was observed for both satellite and laboratory data. Stoner and Baumgardner [51] reported that in mineral soils with iron content above 40 g kg⁻¹ spectral data might be

masked out by the effects of other attributes. It is thus possible that the iron content has a saturation limit in which above it the spectral effect is no longer related to the exact content.

The main problem to the use of iron content for soil classification is its cost, which is double or more than that of routine chemical or granulometric analysis carried out in standard laboratories. This generally leads to the use of qualitative field interpretations such as magnetic attraction in order to reduce these costs. However, this method, despite being useful, does not provide quantitative data and leads to discrepancies as a result of the subjectivity and degree of the pedologists experience. This fact restricts the number of samples for laboratory analysis, and thus reduces the degree of soil map accuracy. In this case, remote spectral sensing, especially in the laboratory, can be used to determine quantitative iron values, which would be useful for soil classification.

The results permit to infer that this technique reduces the costs related to the analysis of this attribute, permitting extended observations in a given area and improving the informative content of the work. Although only detecting surface samples, orbital data, in turn, showed high agreement rates with the original values. Therefore, if on one hand the iron content of the surface layer cannot be used for soil classification, it can be estimated with a high degree of reliability.

In turn, and especially in this study (soils developed from basalt), a close relationship was observed between the soil samples classification obtained from the under-surface and surface in agreement with Hilwig [52]. Therefore, we may infer that the satellite data analysis can help in soil classification. A general agreement of 91.3% was observed here for the different iron content levels obtained with orbital radiometric data, and of 92.2% with laboratory radiometric data. The present study corroborates observations made by Coleman [25].

Table 4. Validation Data. Number of Samples Classified by Iron Contents Based by Both, Laboratory (IRIS Sensor) and Satellite Data

Classes of Iron ^a	Number of Samples Classified Using Traditional Laboratory Analyses ^b	Number of Samples Classified Using Laboratory Spectral Model ^c		Confusion ^f	Number of Samples Classified Using Traditional Laboratory Analyses ^b	Number of Samples Classified Using Satellite Datal Model ^d		Confusion ^f
		(IRIS sensor)				(TM-Landsat)		
		Correct ^e				Correct ^e		
		Number of Samples	%		Number of Samples	%		
Hipoferric (H)	82	79	96,3	3 (M)	84	80	95,2	4 (M)
Mesoferric (M)	14	14	100,0	-	14	14	100,0	-
Ferric (F)	7	2	28,6	5 (M)	5	0	0,0	5 (M)
Total	103	95	92,2		103	94	91,3	

^a Classes of iron used in Brazilian Soil Classification, associated with the contents of iron (sulphuric acid digestion) where their ranges are: Hypoferric (< 80 g kg⁻¹ of Fe₂O₃), Mesoferric (80 a 180 g kg⁻¹ of Fe₂O₃) and Ferric (180 to < 360 g kg⁻¹ of Fe₂O₃); ^b Number of samples with values determined in laboratory (sulphuric acid digestion), in the respective iron ; ^c The data was quantified by using the laboratory spectral model. Then the data was evaluated to look in witch range of iron classification; ^d The data was quantified by using the satellite spectral model. Then the data was evaluated to look in witch range of iron classification; ^e Number of samples and percentage, esteemed by multiple regression equation correct classified in the same iron class as was by the values of iron determined by sulphuric acid digestion; ^fConfusion data. Samples that were classified wrong when compared with laboratory soil analysis.
M = Mesoferric (soil iron classification).

Clay Texture Classes Quantified by Satellite and Laboratory Sensors

The validation procedure for the clay content mapping was similar to the iron above. The accuracy of the satellite and laboratory spectral equations was obtained by looking on the clay classification. The values determined by physical analysis and those estimated by the equations (laboratory and satellite) were classified into the different texture classes and are shown in Table 5.

The traditional laboratory analyses classified 50 samples as sandy, and 31 matched with the spectral laboratory model classification (Table 5), performing accuracy of 62%, 17 samples were confused with medium texture 1. Medium texture 1 has a very close range with sandy class, so this confusion is acceptable. On the other hand, the confusion with medium texture 2 is a significant error. An agreement of 72% was observed for the medium texture 1 class, where 193 samples out of total of 269 were matched. The confusion between sandy and medium 1 texture class is acceptable, mainly if we consider soil management as a practical factor for the clay content. Thus, soil with this similar texture would have similar management.

Relatively high agreement (76%) was observed for the clayey texture, with 1 sample being confused as sandy and 5 samples as medium 2 (Table 5). The lowest agreement (39

%) was observed for the very clayey class, with 31 samples being confused as clayey. It is interesting to note that clayey and very clayey textures are also found very close.

The results obtained for under-surface soil sample based on the laboratory spectral measurements were better than those obtained from the orbital data, with a general agreement of 65% (not taking into account estimated samples with acceptable errors) (Table 5). The orbital data obtained for layer A reached 50% agreement, (not taking into account samples with acceptable errors) (Table 5).

Satellite spectral model presented 50 % agreement with laboratory traditional analyses (Table 5) for sandy texture classification. We had 220 samples classified as sandy texture, i.e., from which 110 samples matched and 90 samples was confused with medium texture 1 (Table 5). Confusion between sandy and medium 1 sample is acceptable since they belong to the same management group. However, if we look on the soil classification level this is incorrect. The largest confusion was observed for values estimated to be of sandy texture, i.e., 70 samples, with this confusion being acceptable as reported earlier in view of the proximity of the texture for these soils. Confusion was also observed for the medium 2 class with 15 samples and for the clayey class with 5 samples, an unacceptable result. Agreement was 48% for the medium 2 class, with 27 samples with determinate value, with 4 samples being confounded with the medium 1

Table 5. Number of Samples Classified for Granulometry Texture. Comparison of Soil Class Texture Obtained Traditional Soil Analyses and by Spectral Laboratory and Satellite Models. Satellite Used Surface Layer for Evaluation; Laboratory Sensor Used Under-Surface Layer for Classification

Texture Class ^a	Number of Samples	Correct		Number of Samples that were Confused with Other Classes of Texture ^b
Samples Classified Using Satellite Spectral Model^c				
	Determined by Traditional Soil Analyses ^d	Determined by Traditional Soil Analyses ^e	%	
Sandy	220	110	50	90 medium 1, 17 medium 2 and 3 clayey
Medium 1	152	62	41	70 sandy, 15 medium 2 e 5 clayey
Medium 2	27	13	48	4 medium 1 e 10 clayey
Clayey	57	51	89	6 medium 2
Very Clayey	17	0	0	16 clayey and 1 medium 2
Total	473	235	50	
Samples Classified Using Laboratory Spectral Model^f				
	VD ^d	N.A. ^e	%	
Sandy	50	31	62	17 medium 1 e 2 medium 2
Medium 1	269	193	72	51 sandy, 24 medium 2 e 1 clayey
Medium 2	49	21	43	3 sandy, 17 medium 1 e 8 clayey
Clayey	54	41	76	1 sandy, 5 medium 2 e 8 very clayey
Very Clayey	51	20	39	31 clayey
Total	473	306	65	

^a Soil class textures: Sandy ($\leq 150 \text{ g kg}^{-1}$ of clay), medium 1 (151 to 250 g kg^{-1} of clay), medium 2 (251 to 350 g kg^{-1} of clay), clayey (351 to 600 g kg^{-1} of clay), very clayey ($> 600 \text{ g kg}^{-1}$ of clay); ^b Confusion samples, classified wrong when compared with values determined in routine analysis; ^c Esteemed values of multiple equation with orbital data, TM-Landsat 5; ^d Number of samples determined (VD) in laboratory (routine analysis), in its respective class texture; ^e Number of samples and percentages esteemed by multiple equation, correctly classified in the same soil class texture as was by the routine soil analysis; ^f Esteemed data by multiple equation obtained by laboratory sensor IRIS.

class and 10 samples with the clayey class. In both cases, some of these data might have been close to the differentiation limit of the texture classes and the result is therefore acceptable. The best results using the satellite data was on the clayey texture classification with 89 % correct (Table 5). The clayey class showed high agreement (89% of the estimated data), with 51 estimated samples being correctly classified out of the total; 57 samples with determinate value, with confusion being observed for 6 samples of class medium 2, which is an acceptable result (Table 5). The very clayey class was completely confounded, with 16 estimated samples being classified as clayey and one sample as medium 2. It is difficult to differentiate these texture classes in the field, especially when the samples showed clay content close to the class limit of 600 g kg^{-1} (Table 5).

Spectral Analysis of Satellite and Laboratory Iron Content and Soil Classification and its Relationship with Soil Survey Map

The total iron spectral map classification determined by spectral laboratory model (Fig. 2b) and the satellite spectral map of iron (Fig. 2a), were compared with the soil map determined by the traditional method (Fig. 2c). Traditional method is performed in laboratory by sulphuric acid digestion. Soil samples have their iron structures completely destroyed, so the total iron can be determined. This type of analysis is time consuming, modify soil components and environment polluter. Iron and texture are classified by the diagnostic B horizon (under-surface). Iron compounds do not vary along depths whereas for some soil classes, clay content do vary. Satellite sensor can only pick the surface layer and laboratory has the opportunity to go under it. Thus, satellite sensor matched more the iron classification, but missed the clay profile variation and hence hamper the texture classification of the soil.

Satellite spectral model determined a predominance of the hypoferric class with 356.30 ha, 75 % of the 473 ha area (Fig. 2a). The LV (laboratory value) soil has similar iron contents from surface until the under-surface soil depth. It performed a 263.80 ha (Fig. 2c). These soils were characterized by a medium texture, close to a sandy texture. The LVA, PA, PVA, RQo and some PV parameters were included in the hypoferric level (Fig. 2a, c). The mesoferric level comprised 115.40 ha, corresponding to about 24.4% of the total study area, matching with medium to clayey and very clayey textural, including LVef, NV, NVef, Cxb and CXef. However, LV with a clayey and very clayey texture was also observed in a small portion. One example is sample 313 with a clayey texture in layer A (540 g kg^{-1}) and a very clayey texture in layer B (700 g kg^{-1}), which was assigned to the mesoferric level. Only sample 364, with 1 ha, occurred in the ferric level for clayey LV, with this level not being observed in the under-surface layer.

The iron distribution using laboratory spectral model presents a similar distribution with satellite model (Fig. 2a, b), with a predominance of the hypoferric class with 355.43 ha, corresponding to about 75% of the total study area, with the same soils as described for layer A.

This finding justify the low variability of iron between surfaces. A more significant difference was observed for values in the area of the mesoferric level (104 ha and 115 ha

area obtained for laboratory and satellite spectral models, respectively). On the other hand, the area of the ferric level was increased in the map, from 1 ha to 13 ha. In fact, the more clayey soils determined by traditional soil map (Fig. 2c), presented a higher iron content. Thus, in these cases, the satellite spectral model did not completely match with real truth.

However, the data estimated by laboratory spectral model and classified for the iron levels, especially, the LVef, NVef and CXef units were found to be reduced in the mapped area, with a concomitant increase in the areas of the LV, NV and CXb classes, without the ferric class (Fig. 2b, c). A good example is the mapping unit of LVef with 11 ha (within the rectangle in Fig. 2c), where various samples showed a ferric character (Fig. 2b). However, for the same area (Fig. 2b), only sample 195 was found in the ferric level in the map, thus reducing the area of LVef to be only 1 ha. In this respect, the iron values estimated from laboratory spectral model, together with delimitation techniques for the mapping units, might contribute to the refinement of the limits of some soil classes.

CONCLUSIONS

It is possible to estimate the absolute content of Fe_2O_3 , Al_2O_3 , SiO_2 , TiO_2 , clay and the $\text{Al}_2\text{O}_3/\text{Fe}_2\text{O}_3$ ratio based on spectral information acquired in both laboratory and satellite domains by multiple linear regression models using the electromagnetic radiation in the VIS-NIR-SWIR region.

The results indicate that there is no need to elaborate independent models for each soil sampling depth, which would be more difficult to put into practice. However, it was found to be important to analyze samples representative of the whole study area.

Quantitative evaluation of spectral reflectance permits the acquisition of Fe_2O_3 and clay data as a basis for soil mapping and classification.

The findings of the present study indicate that orbital sensors can quantify soil attributes related to soil classification, such as clay and Fe_2O_3 mostly on the soil surface. Laboratory sensors for sure enlarged better results, due to the control of external factors. Although, the implement of the methodology will depend on the objectives of the work. Satellite can improve information from distant areas, but has the problem to read only surface soil layer. Laboratory conditions have the vantage to control external factors and take readings of various soils layers (surface and under-surface).

Soils attributes have influence in specific wavelengths, although also interfere in all spectrum. This explains why the use of multiple regression acquire important results. On the other hand, this methodology can only be improved if patterns of different soils in different regions be developed. An automatic procedure on the determination of models and quantification of unknown soil samples has to be improved.

This type of methodology can have several vantages in relation to traditional analysis, such as environmental quality, less cost for humanity, quick information, enlarge soil survey and land use planning.

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