Problems - current state - the future perspectives

Soil Maps * Today: none

* Method: traditional. Mostly Inserted elevation model.

* Spectroscopy has not been used

Why?

$

Uncertainty on the methodology

NECESSITY TO CONVINCE:

THE BIG PICTURE

SOIL MAPS DERIVED FROM THIS TECHNOLOGY

Create a method. A strategy.

What to do.

Prepare a data bank for users.

Problems - current state - the future perspectives

Soil Monitor

* Today: few…none
* Method: traditional. Laboratory analysis
* Spectroscopy has not been used

Why?

How can a government control center use
the sensor to monitor Hg (example), if we still do not have a universal pattern?
How can they believe in this?
It's a matter of time….and method.

What to do.

Prepare a data bank for users.

Create a method.
A strategy.

Problems - current state - the future perspectives

Precision Agriculture
With real time sensors

* Today: zero

* Method: traditional.
* Laboratory analysis.

* Users are really wanting this!

Soil analysis too high and time from field collection to lab and again to tractor is time-consuming

Why?

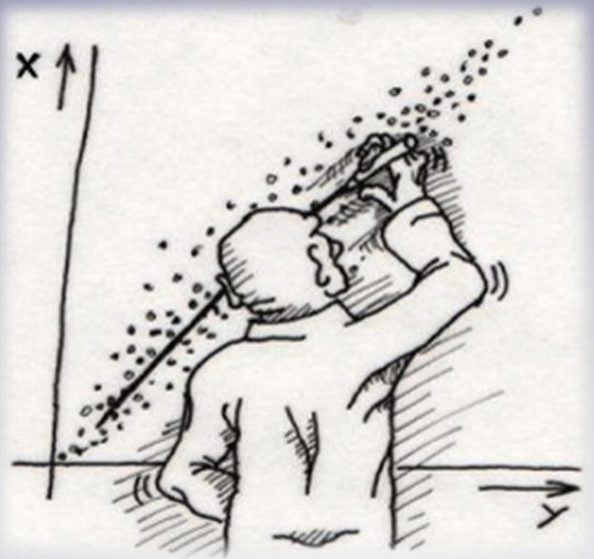
* Soils at field varies. Sensors get information from moist, leaves, rocks…..
* Sensors are constantly blocked by soil during the scan underground..

* Soil information for fertilizer like N, P, pH, Ca, Mg, K, P, are too hard to be detected by sensors.

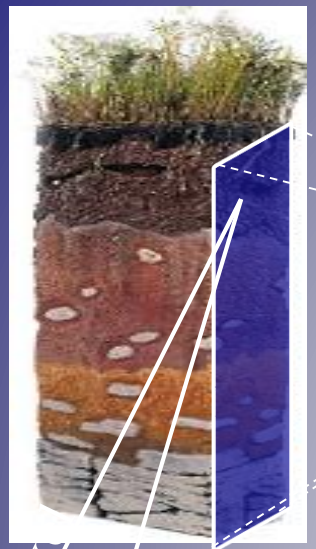
What to do.

More Research

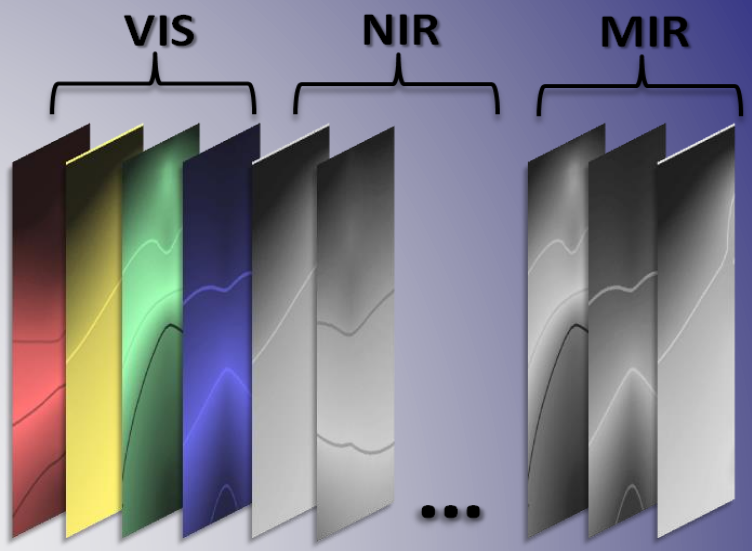
Insert the technology in
Undergraduate universities
As obligatory disciplines
In Agronomy; Geography….

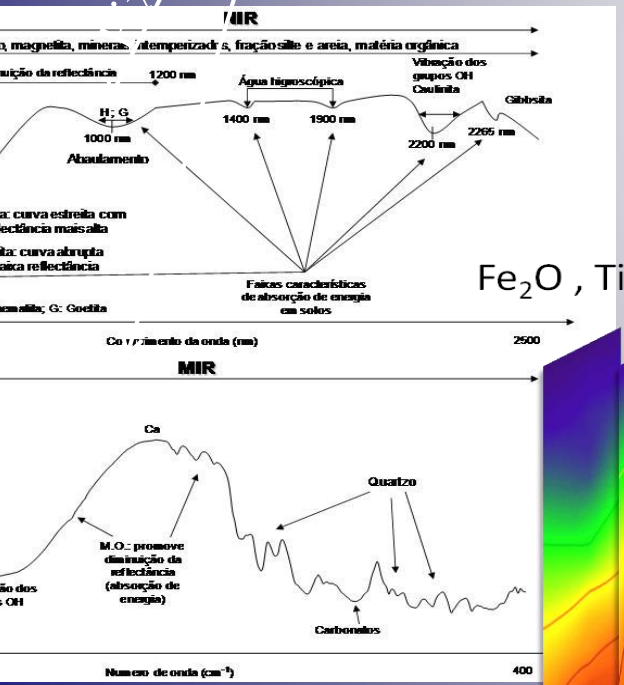


Efforts to breakdown prices of sensors. In 1995: $60.000 ; today: $60.000

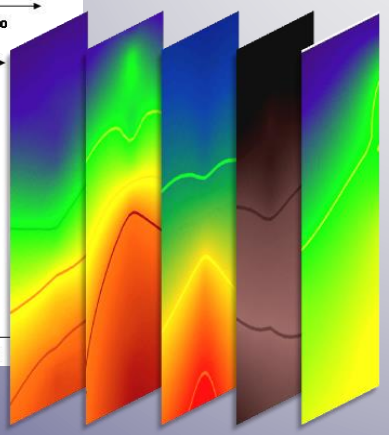


Sensoriamento proximo usando camaras hiperespectrais



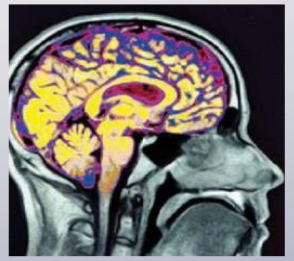


Fe_2O , TiO_2 , Al_2O_3, Cor, etc



Conhecimento experto

+

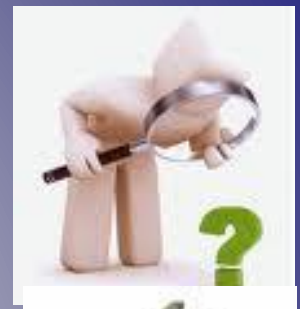


≈

Determinação *in situ* da classe e das características do sol

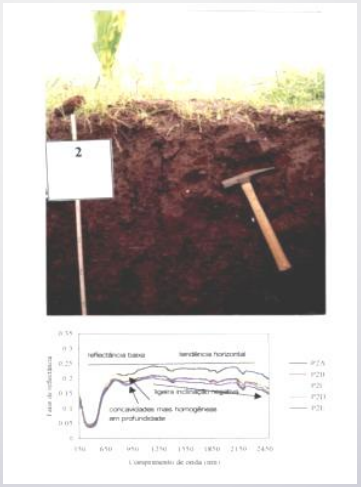
Problems - current state - the future perspectives

Spectral Sensing Tecnology



$

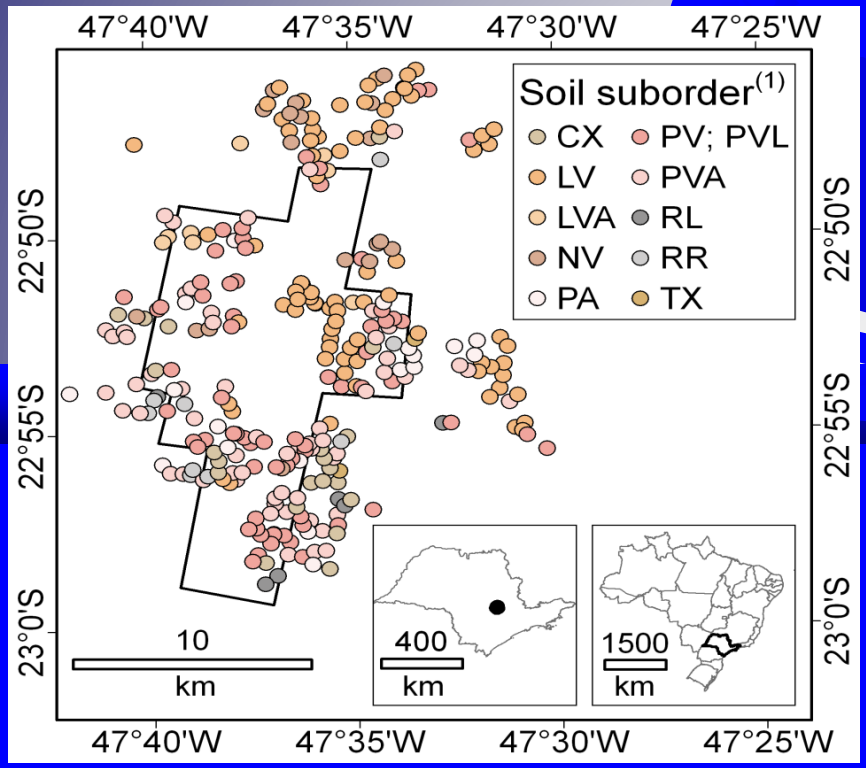
It is not a robust equipmment for hard field works



Make the database

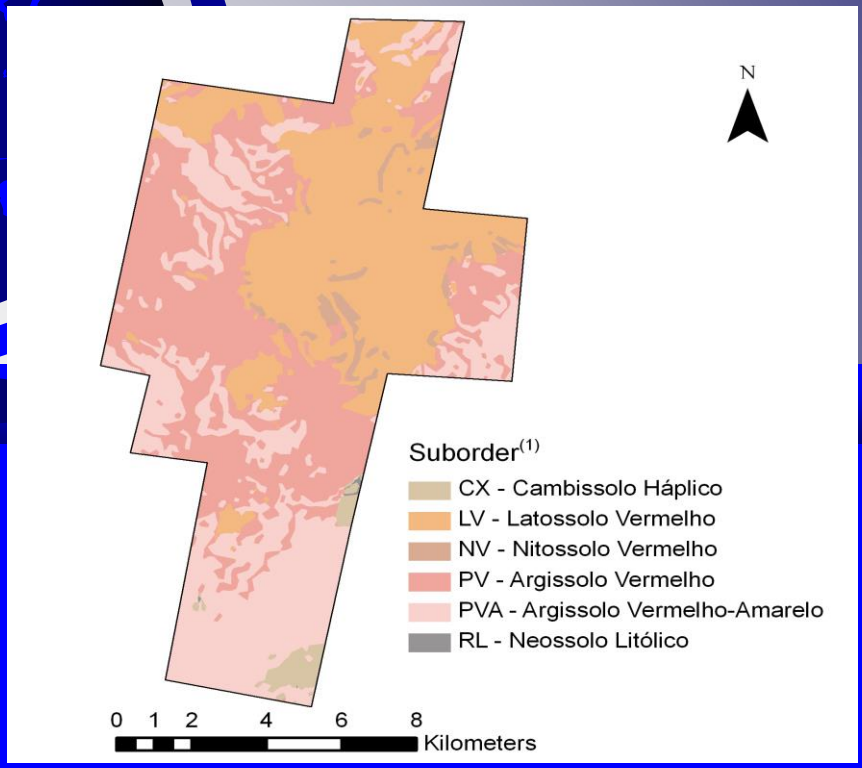
Assess information

289 training + 47 validation soil profiles in 13,000 ha under sugarcane in São Paulo, Brazil



Multinomial logistic regression based on:

b) GIS variables + Soil VisNIR at 3 depths



Up to 53% validation agreement for Red Latosols at the suborder level

All models selected VisNIR reflectance as predictor

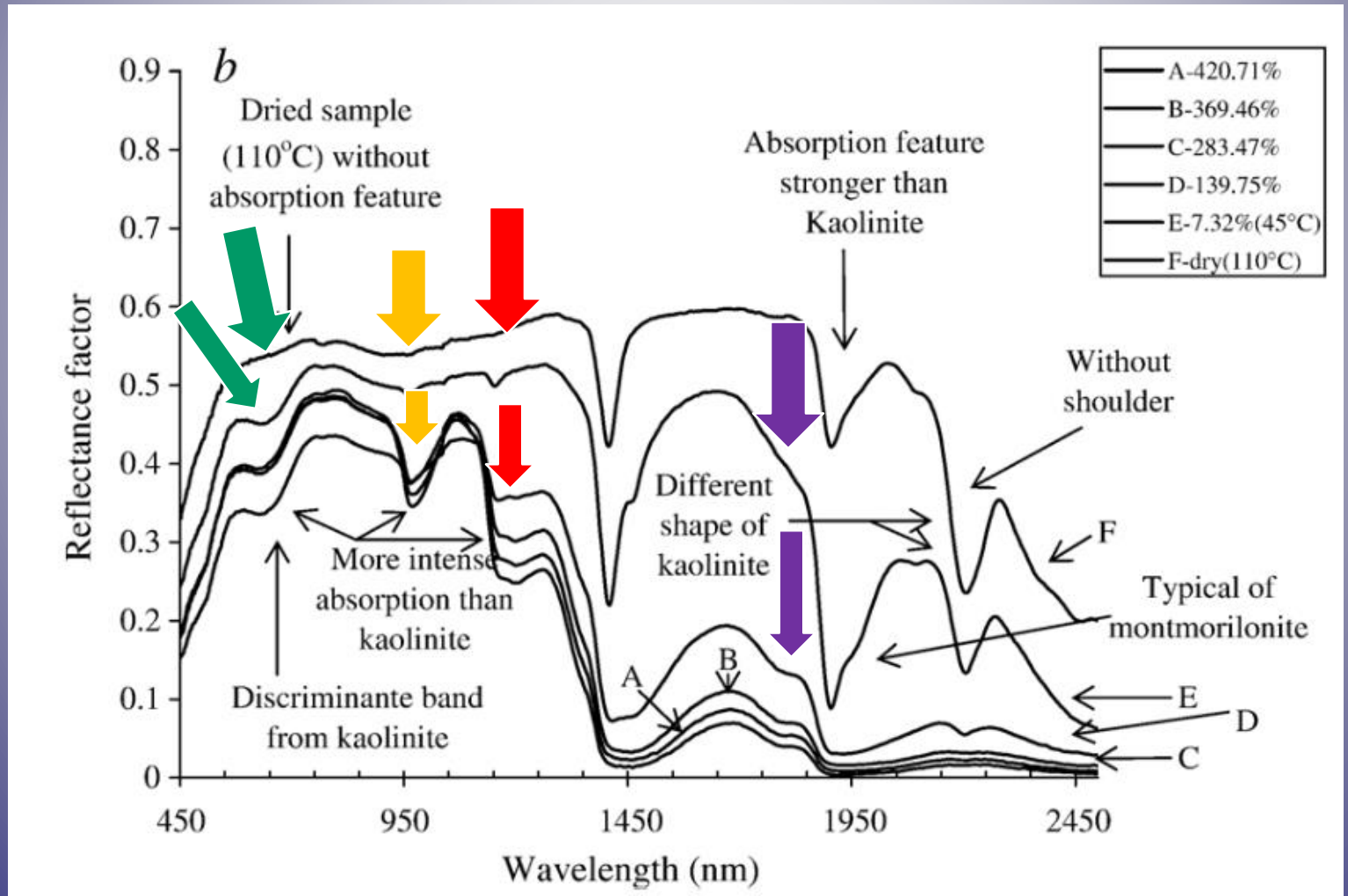
Vasques, G.M., Demattê, J.A.M., Viscarra Rossel, R.A. *et al*., Geoderma, *submitted*

Determining soil water status and other soil characteristics by spectral proximal sensing

J.A.M. Demattê [a,*], Antonio A. Sousa [b], Marcelo C. Alves [b], Marcos R. Nanni [c], Peterson R. Fiorio, Rogério Costa Campos [d]

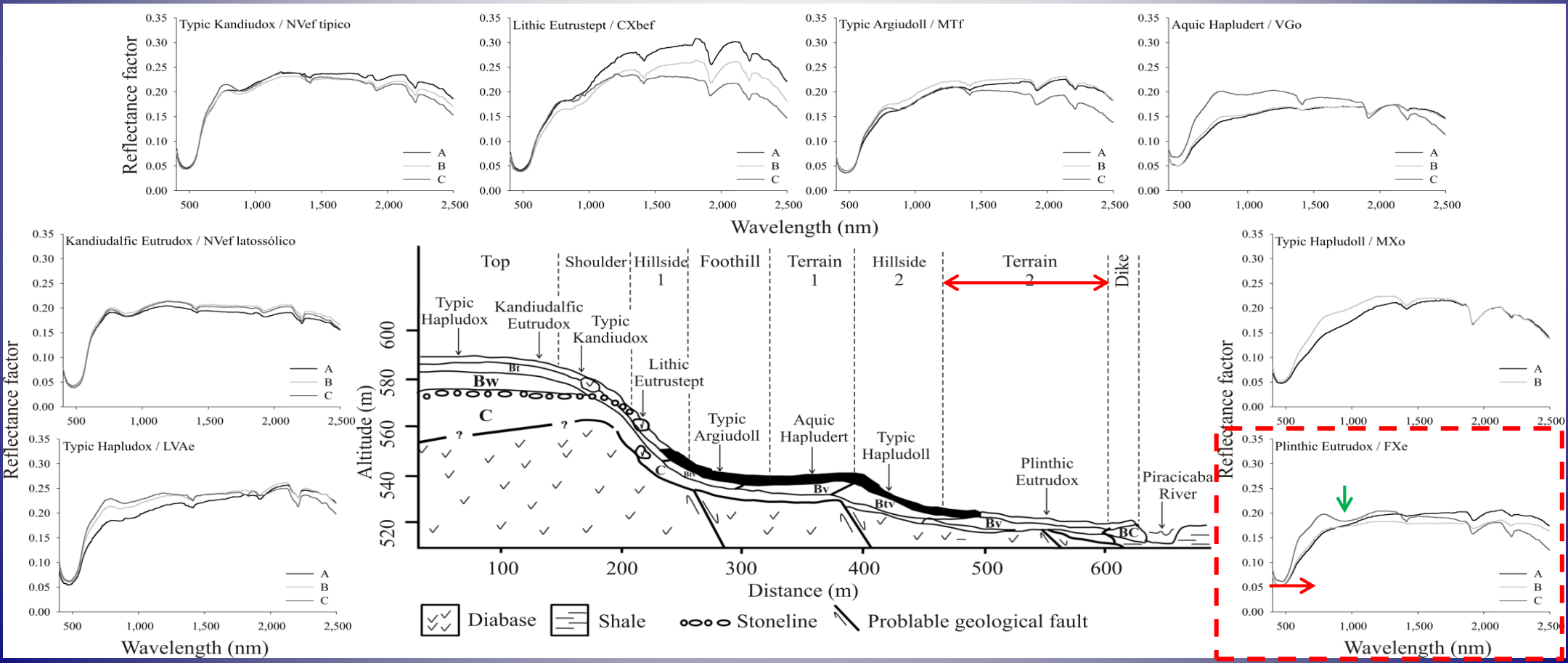
Geoderma 135 (2006) 179 – 195

Importance of moist for identification of minerals in soils



Soil profile spectral **transformation** along the **toposequence** (≠ **pedogenesis**)

- **End** of the toposequence (2nd **Terrain**)
- Spectral behavior **similar** to the Aquic Hapludert (**same** landscape **position** and **drainage** conditions)
- **Difference**: spectrum of **layer C** with **higher content** of **crystalline** iron oxide



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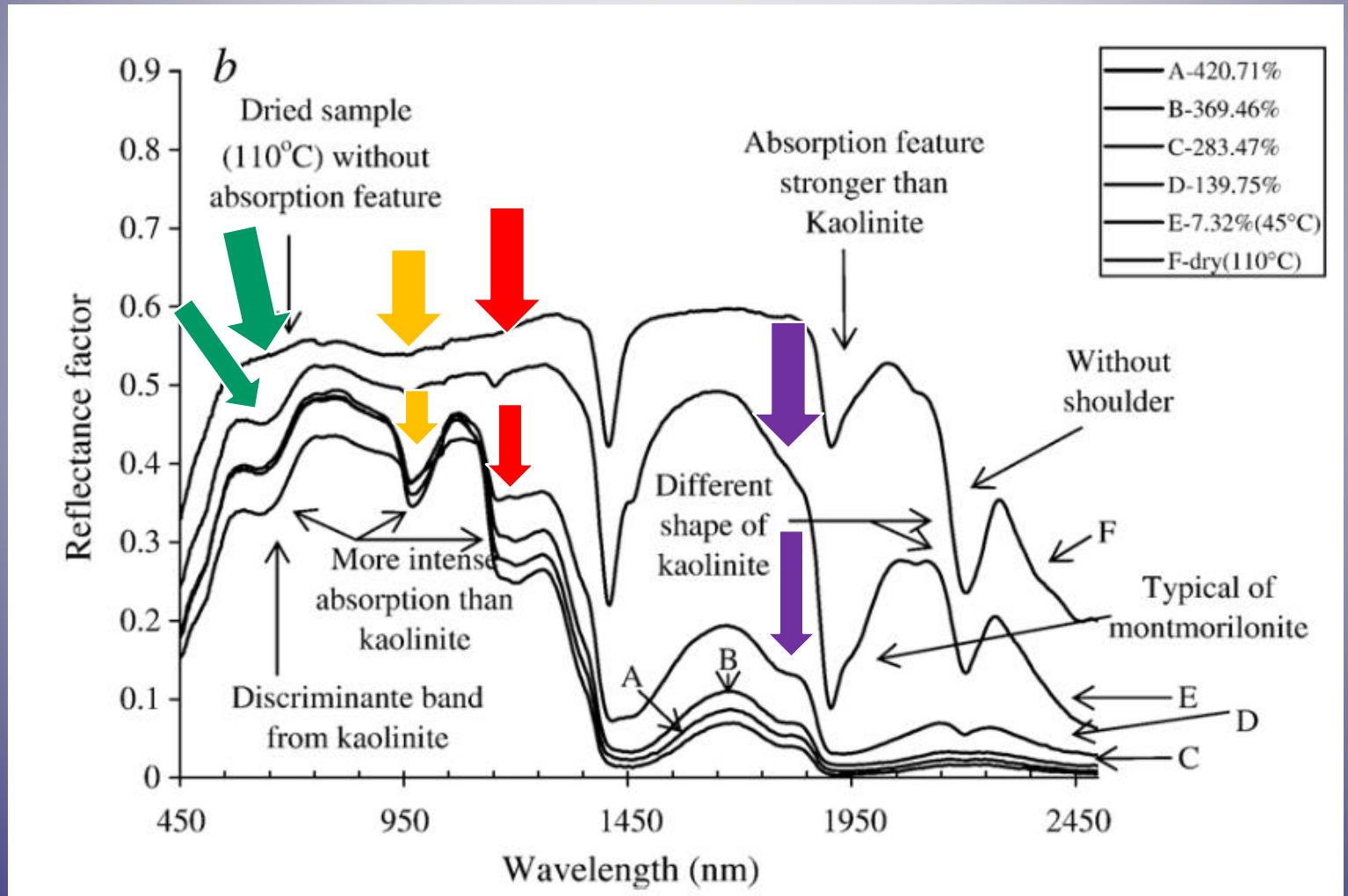
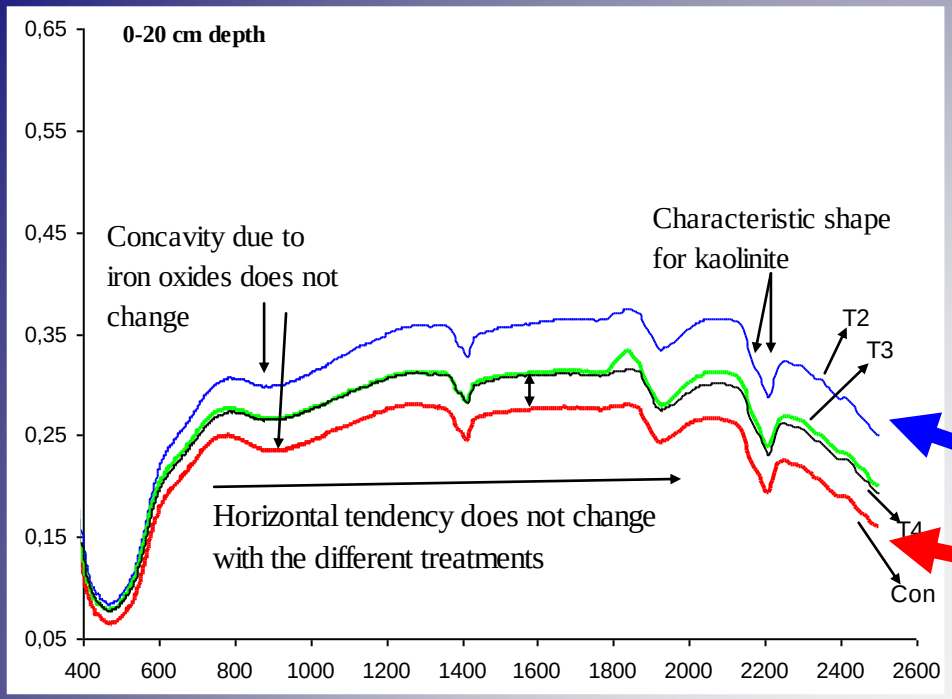
Geoderma 135 (2006) 179 – 195

moist IS IMPORTANT for Mineral identification





Soil with vinasse

Soil without vinasse

Treatments	0 – 20 cm depth
	K
	$mmol_c\ dm^{-3}$
T1	0.37a
T2	2.57ab
T3	4.9b
T4	8.63c

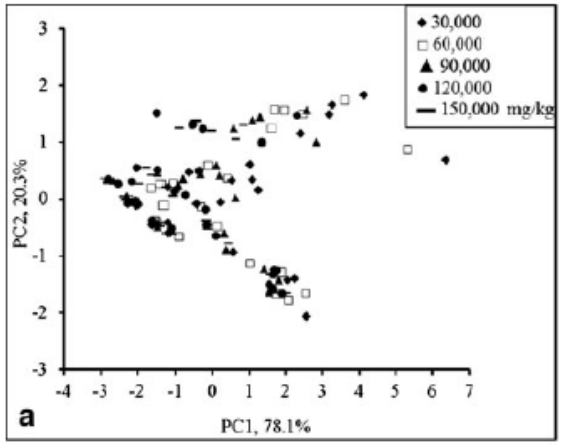
Effect of fermentation residue on the spectral reflectance properties of soils

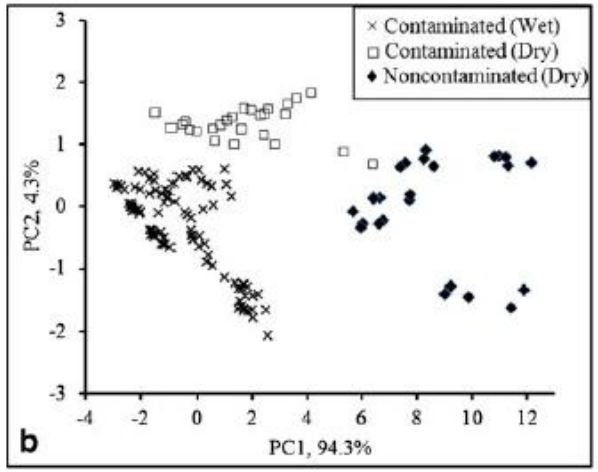
J.A.M. Demattê[a,*], M.A.P. Gama[a], M. Cooper[a], J.C. Araújo[b], M.R. Nanni, P.R. Fiorio[a]

Geoderma 120 (2004) 187–200

Combined Effects of Oil Concentration, Clay and Moisture Contents on Diffuse Reflectance Spectra of Diesel-Contaminated Soils

Reuben N. Okparanma · Abdul M. Mouazen





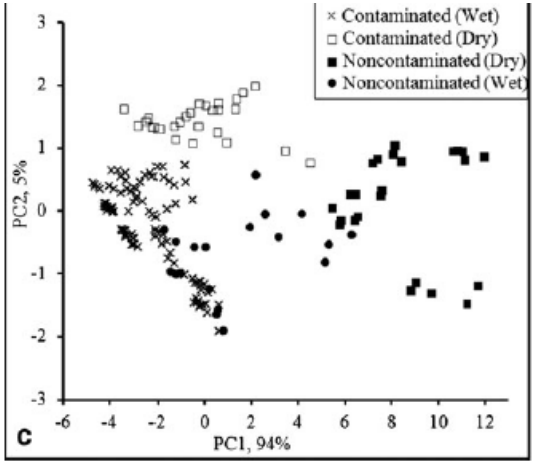
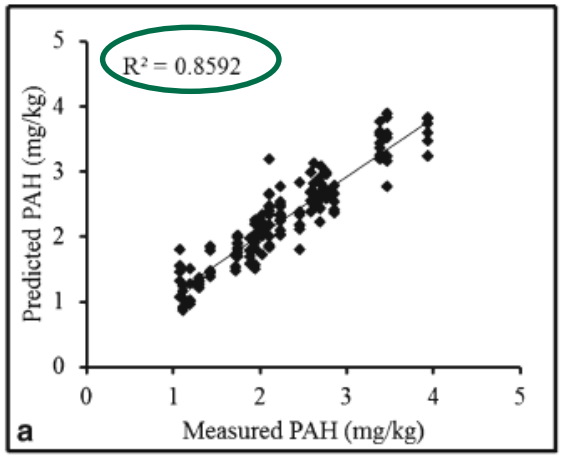


Fig. 5 Principal component analysis scores plots of visible and near infrared diffuse reflectance spectra of overall dataset evaluated for diesel-contaminated and non-contaminated (wet and dry) soils

PCA may only be used to differentiate the samples into contaminated and non-contaminated as well as dry and wet groups as it could not be used to account for the different levels of oil contamination in the samples.



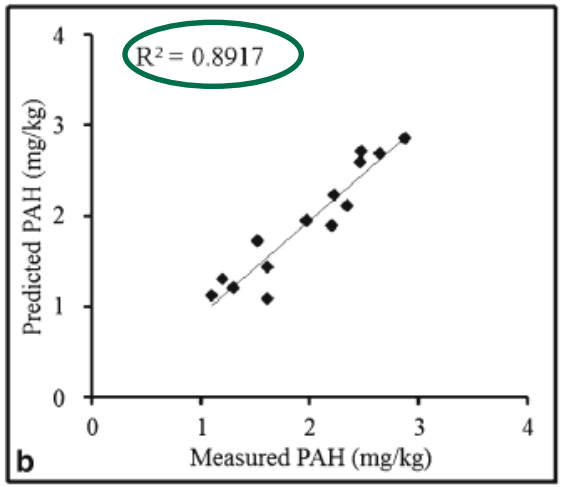
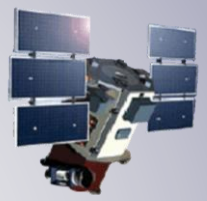


Fig. 3 Scatter plot of chemical versus visible and near infrared spectroscopy predicted values of polycyclic aromatic hydrocarbons (*PAH*) using partial least squares models developed with 150 soil samples and validated with a cross-validation (135 samples) and b validation (15 samples) sets

Water Air Soil Pollut (2013) 224:1539
DOI 10.1007/s11270-013-1539-8

by satellite sensor

Attribute	Multiple equations[1]	r^2
Sand	$Sand^{0,5} = 13,54 + 0,934*TM\_B1 - 0,228*TM\_B5 + 0,663*TM\_B7$	0,5245
Clay	$clay^{0,5} = 27,03 - 1,260*TM\_B1 + 0,363*TM\_B3 - 0,301*TM\_B4 + 0,305*TM\_B5 - 0,848*TM\_B7$	0,6752
Silt	-	-
Organic matter	$O.M.^{0,5} = 7,084 - 0,109*TM\_B7 - 0,102*TM\_B2$	0,5081
Silt/Clay	$Log_{10}\ SilCl = -0,721 + 0,0566*TM\_B1 + 0,0174*TM\_B7$	0,5614
Sum of cations	$Log_{10}\ S = 2,550 - 0,08*TM\_B7 - 0,032*TM\_B3 + 0,0369*TM\_B5$	0,4919
CEC	$Log_{10}\ CTC = 2,581 – 0,06*TM\_B7 - 0,014*TM\_B3 + 0,0218*TM\_B5$	0,5510
T	$T^{0,5} = 3,045 - 0,190*TM\_B3 + 0,0839*TM\_B1 + 0,300*TM\_B2$	0,1372
m %	$m\% = -0,237 + 1,697*TM\_B1$	0,1060
V %	$V^{1,5} = 613,2 - 14,96*TM\_B3 – 32,14*TM\_B1 + 30,52*TM\_B5 - 37,68*TM\_B7$	0,1976
SiO_2	$SiO_2^{0,5} = 13,28 - 0,450*TM\_B1 + 0,252*TM\_B5 - 0,598*TM\_B7$	0,5975
Fe_2O_3	$Log_{10}\ Fe_2O_3 = 2,820 - 0,118*TM\_B1 - 0,058*TM\_B7 + 0,011*TM\_B5$	0,7248
TiO_2	$Log_{10}\ TiO_2 = 2,191 – 0,104*TM\_B1 - 0,044*TM\_B7$	0,7273



0.67

0.55

0.59

0.72

0.72

[1] significative at 1 % levels; " – " not determined. Nanni and Demattê (2006) SSSAJ

Nanni and Demattê (2006)

by laboratory sensor

Attribute	Multiple equations[1]	r^2	
Sand	Sand = 223,4 - 9134*BD18_HA [illegible] D22_HA + 240,9*BD2_HA - 3152*BD4_HA +2494*BD7_HA [illegible] D9_HA	0,7442	
Clay	$Clay^{0,5}$ = 21,78 – 94,05[illegible] + 468,4*BD18_HA - 462,9*BD19_HA + 343,5*[illegible] - 361,2*BD22_HA + 70,32*BD4_HA - 125,8*BD6_H[illegible]4*BD7_HA+34,86*H2_HA+ 51,50*H3_HA - 119,5*H9_HA	0,9152	0.9
Silt	Log_{10} Silt = 2,407 – 6,14[illegible]A + 4,762*BD17_HA + 9,984*H1_HA	0,2694	
Organic matter	O.M. = 36,78 – 1046*BD11_HÁ + 1028*BD12_HA - 773,1*BD17_HA - 100,8*BD2_HA - 319,0*BD5_HA + 1093*BD9_HA – 672,1*H11_HA - 757,1*H12_HA + 720,8*H13_HA – 474,1*H3_HA - 274,2*H4_HA – 394,5*H5_HA + 964,7*H6_HA + 309,9*H7_HÁ	0,7974	
Silt/Clay	Log_{10} Silt/clay = - 0,703 -10,86*BD17_HA - 3,979*BD19_HA - 0,739*BD1_HA + 17,37*BD22_HA + 1,163*BD2_HA - 0,488*BD4_HA + 9,226*H8_HA	0,7780	
Sum of cations	$S^{0,5}$ = 11,92 - 375,3*BD13_HA + 323,7*BD14_HA + 388,9*BD18_HA - 343,0*BD22_HA - 179,4*BD1_HA + 84,60*BD4_HA + 96,21*BD6_HA + 350,0*BD8_HA - 342,5*BD9_HA – 38,7*H1_HA - 167,8*H2_HA - 55,13*H3_HA	0,8759	0.87
CEC	Log_{10}CTC = 2,409 - 40,56*BD13_HA + 38,46*BD14_HA + 26,39*BD18_HA - 25,29*BD22_HA - 19,53*BD2_HA + 9,452*BD3_HA + 25,94*BD8_HA - 18,00*BD9_HA - 11,92*H1_HA - 9,500*H2_HA - 3,967*H3_HA - 7,862*H4_HA + 6,914*H8_HA	0,9098	0.9
V %	V^2 = 7896 - 68781*H11_HA - 17945*H2_HA + 46992*H8_HA	0,2927	
SiO_2	$SiO_2^{0,5}$ = 10,34 - 193,3*BD16_HA + 443,9*BD18_HA – 275,6*BD19_HA + 38,37*BD4_HA +164,8*H10_HA + 174,2*H12_HA - 77,12*H1_HA + 18,30*H4_HA	0,9258	0.92
Fe_2O_3	Log_{10} Fe_2O_3 = 2,389 + 5,341*BD11_HA - 6,102*BD22_HA + 2,616*BD1_HA - 4,124*BD6_HA - 0,886*BD7_HA - 22,04*H11_HA + 6,716*H2_HA - 2,591*H9_HA	0,9501	0.95
TiO_2	Log_{10} TiO_2 = 1,513 + 2,399*BD12_HA - 15,54*BD16_HA + 8,101*BD22_HA + 0,888*H1_HA + 6,480*H2_HA + 6,630*H4_HA + 6,527*H5_HA - 5,798*H8_HA - 23,74*H11_HA + 29,03*H13_HA	0,9519	0.95

[1] significative at 1 % level

Nanni and Demattê (2006) SSSAJ

Nanni and Demattê (2006)

System for Sattelite conditions

Image processed: atmospheric correction, transformed to reflectance and Georeferenced

METHODOLOGY TO DETECT BARE SOIL

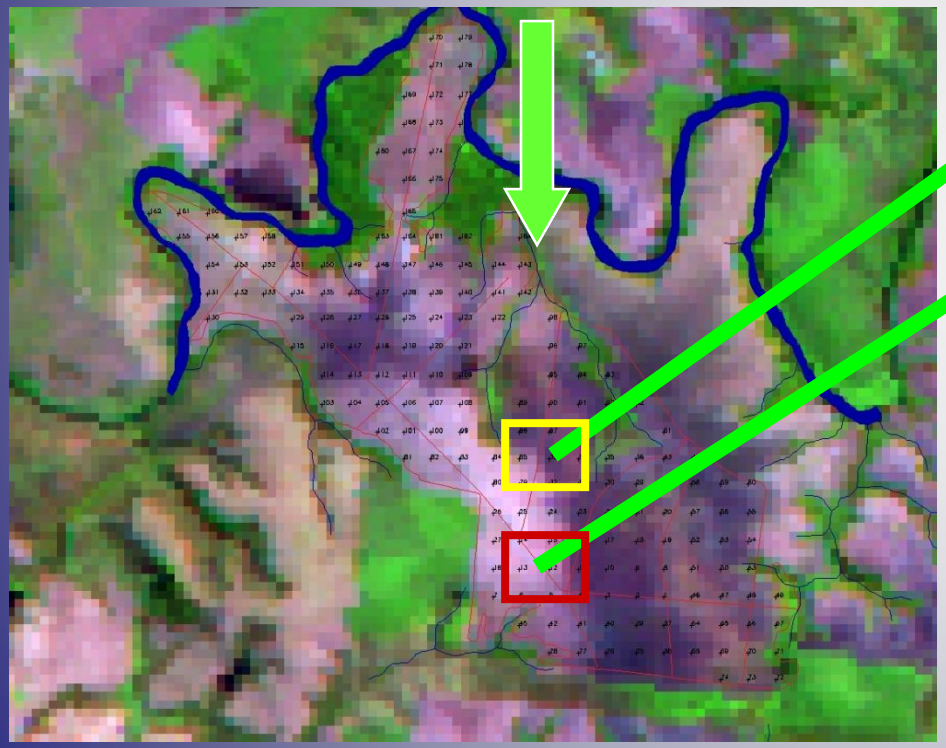
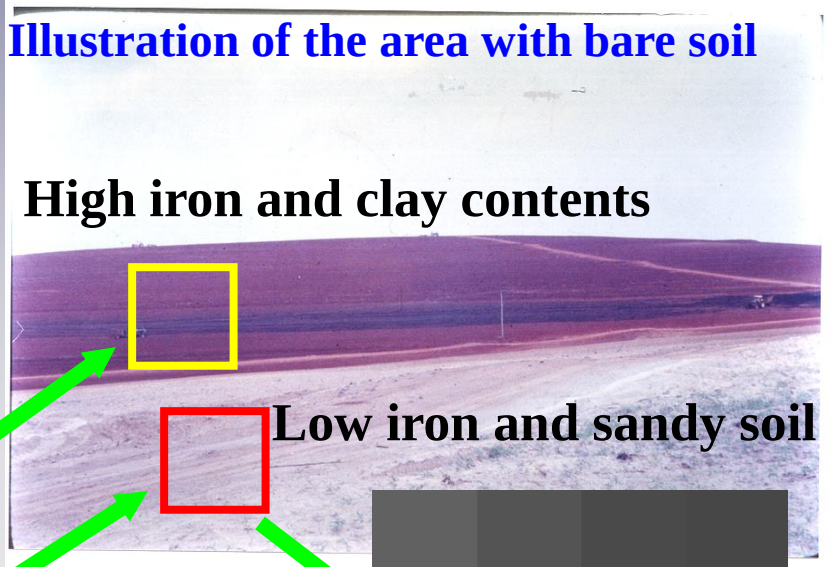
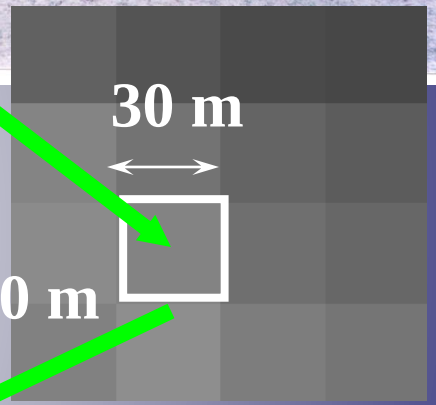
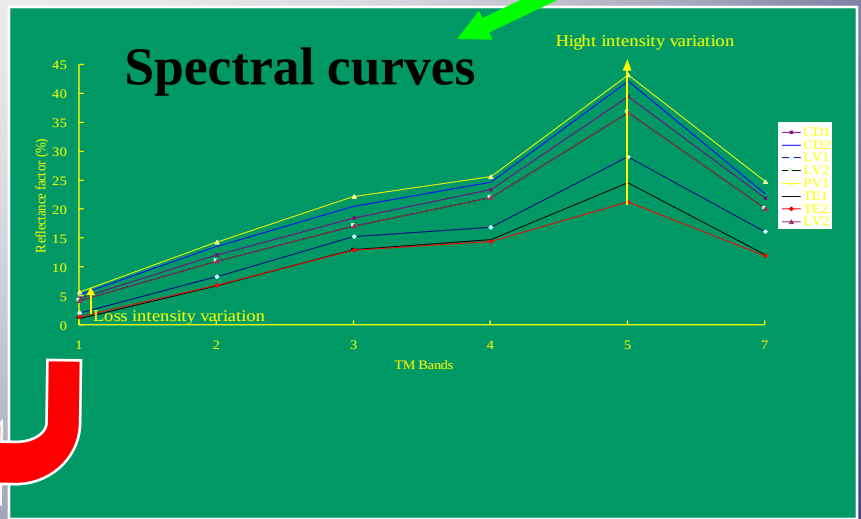


Illustration of the area with bare soil







Modelize data

SOIL
3.

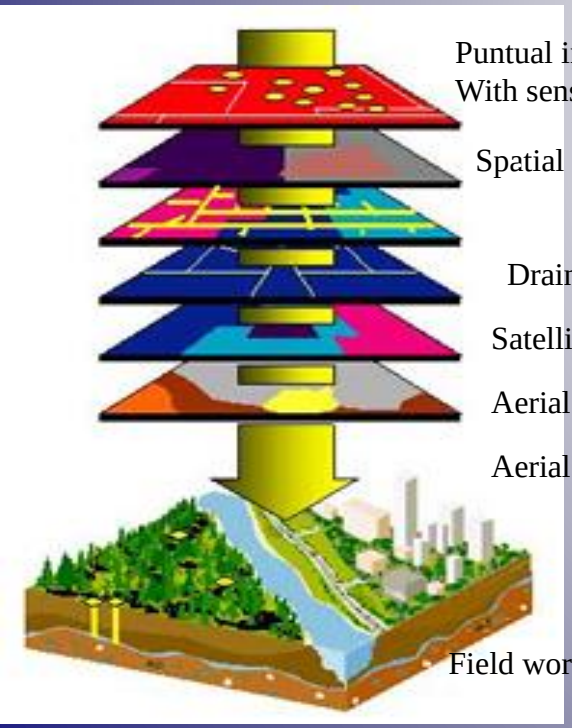
Table 3
Summary of PLSR results for the twelve soil properties dataset.

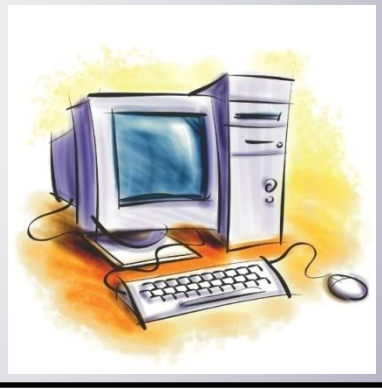
Property	Unit	Range (nm)	Pre-treatment	PC[a]	N[b]	Calibration			Prediction					Category[c]	
						R_{cal}	R^2_{cal}	$RMSE_{cal}$	R_{val}	S.D.	R^2_{val}	$RMSE_{val}$	RPD	This paper	Previous
MC	wt. %	500–1600	2nd Derivative	6	130	0.97	0.95	1.23	0.96	5.11	0.93	1.42	3.6	A	A
SOM	wt. %	500–1600	2nd Derivative	6	130	0.96	0.92	0.30	0.95	1.02	0.90	0.35	2.9	A	A
pH	pH unit	500–1600	Smth and 2nd-D[d]	6	130	0.88	0.78	0.19	0.83	0.37	0.69	0.23	1.6	B	A
EC	mS cm^{-1}	500–1600	2nd Derivative	4	130	0.80	0.64	0.02	0.77	0.02	0.60	0.02	1.3	C	B
CEC	me $100g^{-1}$	500–1600	2nd Derivative	6	130	0.96	0.92	1.25	0.94	4.08	0.89	1.44	2.8	A	A
C–t	%	500–1600	2nd Derivative	5	130	0.95	0.91	0.13	0.94	0.42	0.89	0.15	2.9	A	A
N–a	mg $100g^{-1}$	500–1600	2nd Derivative	8	130	0.89	0.79	0.12	0.83	0.23	0.69	0.15	1.6	B	C
N–h	mg $100g^{-1}$	500–1600	2nd Derivative	9	130	0.89	0.77	0.44	0.81	0.84	0.65	0.56	1.5	B	A
N–n	mg $100g^{-1}$	1100–1650	2nd Derivative	5	130	0.71	0.50	0.14	0.67	0.15	0.45	0.15	1.0	C	C
N–t	%	500–1600	2nd Derivative	5	130	0.94	0.89	0.01	0.93	0.03	0.87	0.01	2.6	A	A
P–a	mg $100g^{-1}$	500–1600	2nd Derivative	4	130	0.87	0.76	7.46	0.85	14.35	0.72	8.00	1.8	B	B
PAC	Non	500–1600	2nd Derivative	6	130	0.96	0.92	42.02	0.95	142.75	0.90	47.94	3.0	A	–

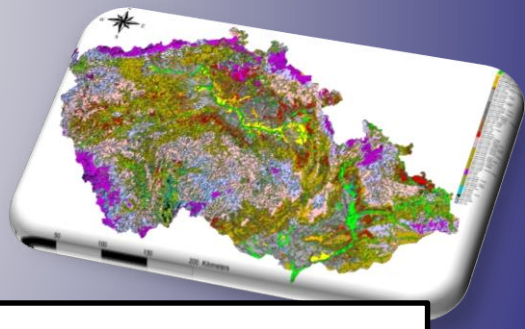
[a] Number of PLSR factors used in the model.
[b] Number of samples used in the model.
[c] Category of prediction (full cross-validation) ability of PLSR for parameters. A: RPD>2.0; B: RPD=1.4–2.0; C: RPD<1.4 (Chang et al., 2001).
[d] Smoothing and 2nd derivative.

Sequence of Work and Main Goal

Thematic information + **Tradicional Studies** + **Statistical Techniques** → **Digital Soil Maps**

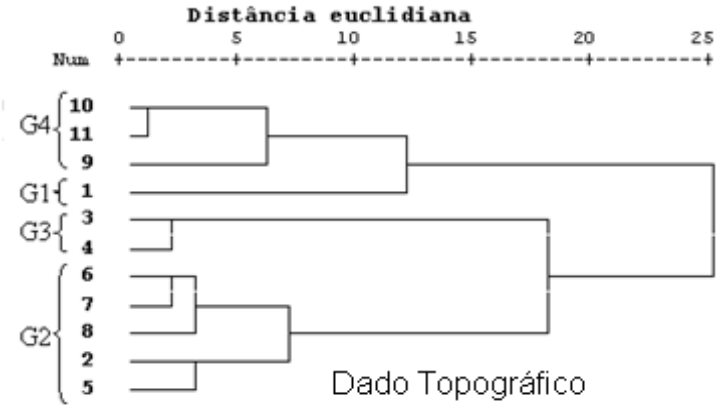


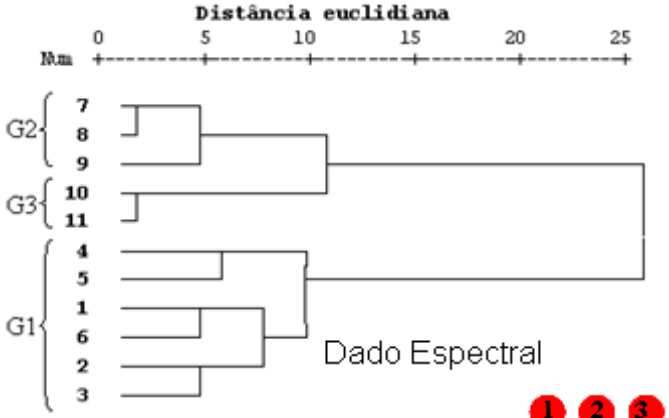


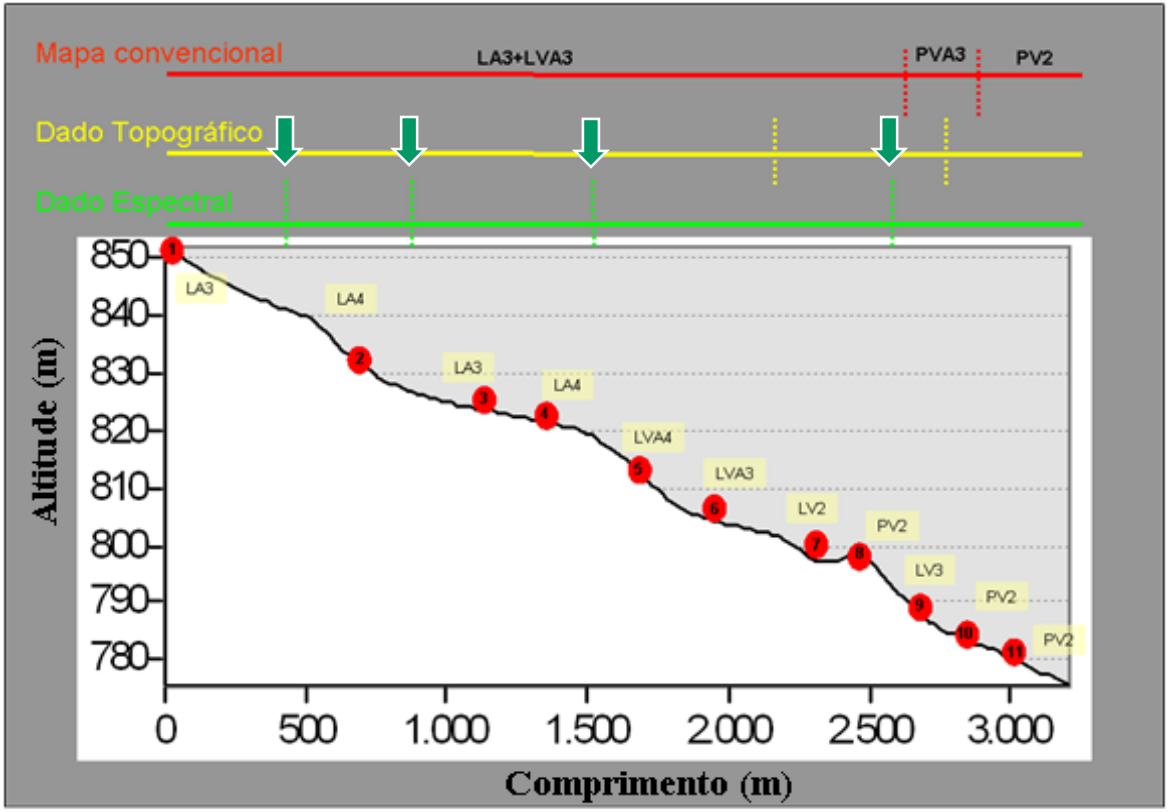


Typical and important **morphological properties** of vertisols (**slickensides** and **cracks**) **undetectable** by reflectance spectroscopy

Detection of Soil limits by conventional method (RED), by topography YELLOW), and spectroscopy (GREEN)







Legenda:

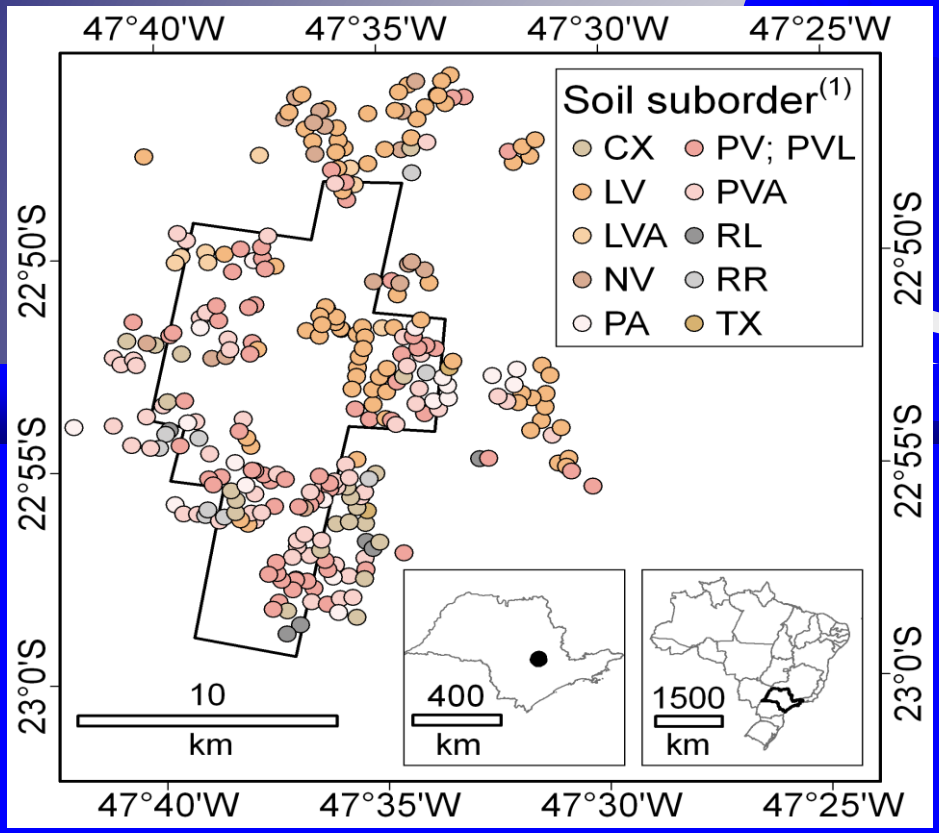
1 2 3 Locais de tradagem com as respectivas classificações pontuais

Limites das unidades de mapeamento com base no mapa semi detalhado

Spectroscopy allowed a more detailed detection of soil limits
Not always topography is the best parameter foi soil discrimination

J.A.M.Demattê, M.Alves, B.C. Gallo (2014-in press Brazilian Journal of Soil Science)

202 training + 89 validation soil profiles in 13,000 ha under sugarcane in São Paulo, Brazil



Multinomial logistic regression and principal component analysis based on:

a) Soil VisNIR spectral curves at 3 depths

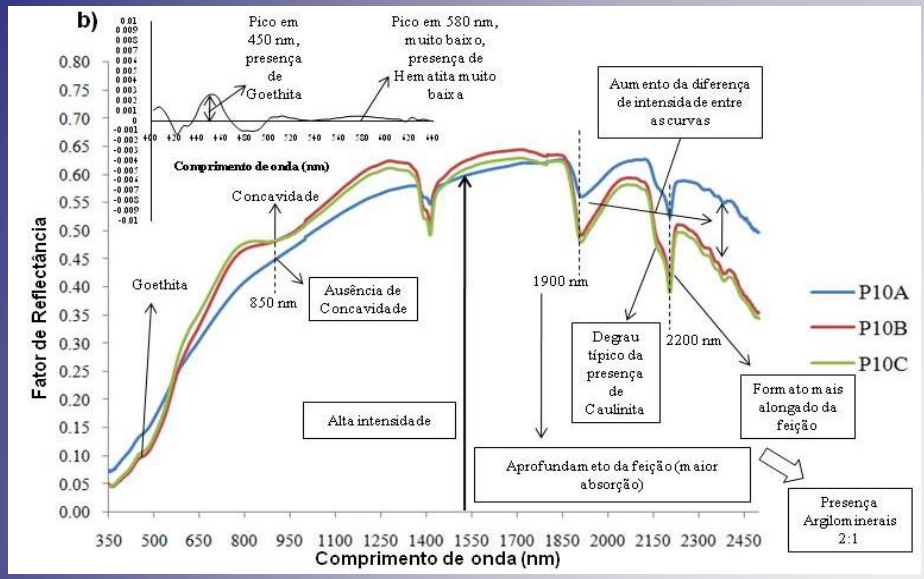
Up to 69% validation agreement for Red Latosols at the suborder level

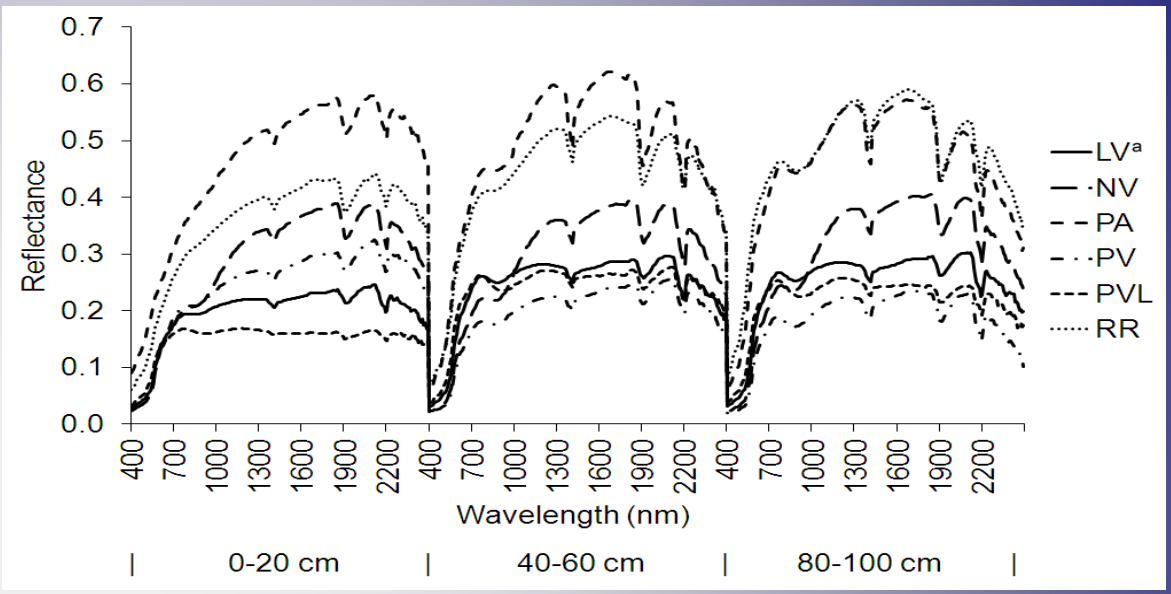
Up to 86% validation agreement for Latosols at the order level

(Geoderma, submitted 2013)

Soil Classification by spectral morphology interpretation

Demattê, J.A.M. & Bellinaso , H. (2013 – in submisssion)





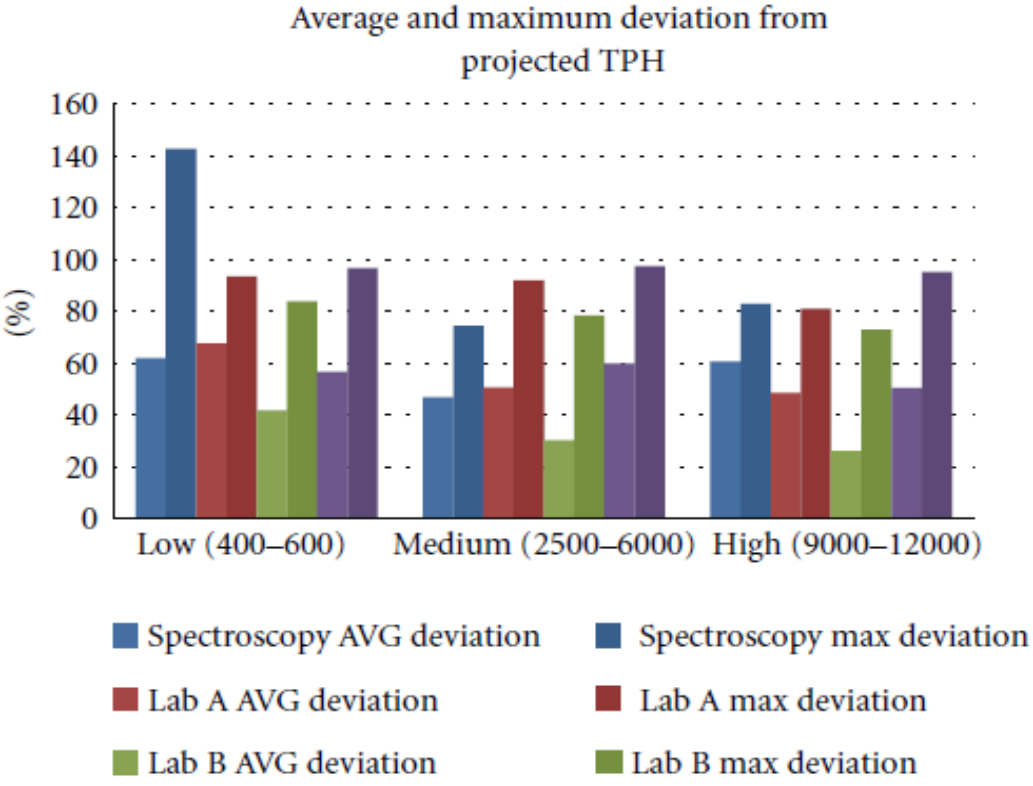
Número de Perfis	Order level classification		Second order classification		Third order clasification		With Texture		With Iron	
	nº	%	nº	%	nº	%	nº	%	nº	%
Utilizando Técnicas de Sensoriamento Remoto (atributos preditos)										
13	11	85	11	85	6	46	9	69	12	92

Research Article

Quantitative Analysis of Total Petroleum Hydrocarbons in Soils: Comparison between Reflectance Spectroscopy and Solvent Extraction by 3 Certified Laboratories

Guy Schwartz,[1,2,3] Eyal Ben-Dor,[2] and Gil Eshel[4]

Applied and Environmental Soil Science
Volume 2012, Article ID 751956, 11 pages
doi:10.1155/2012/751956



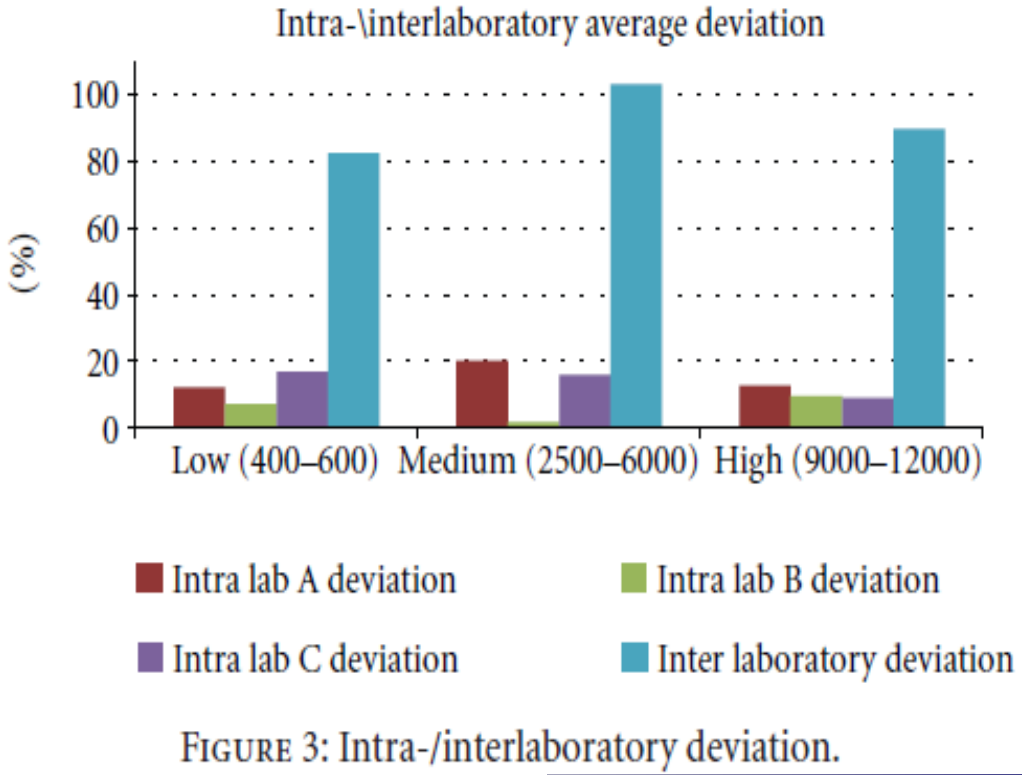
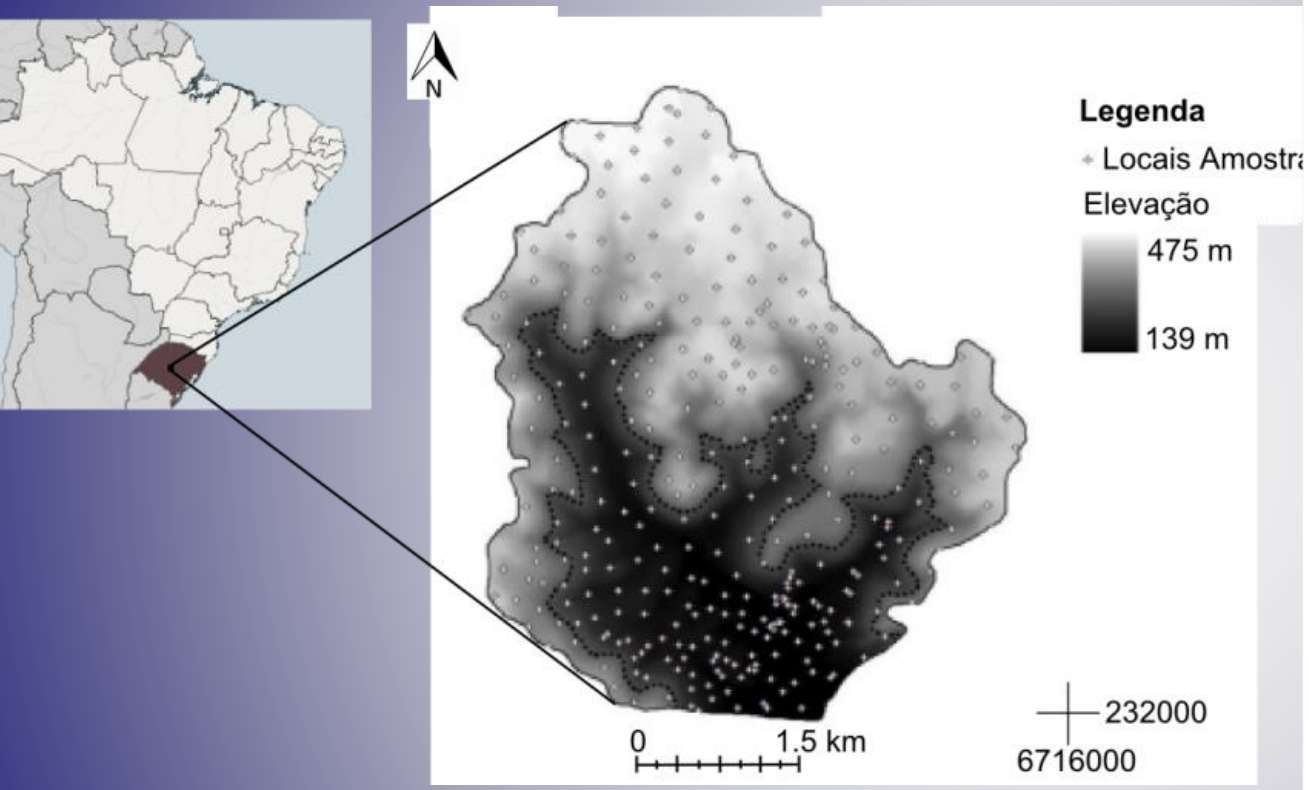


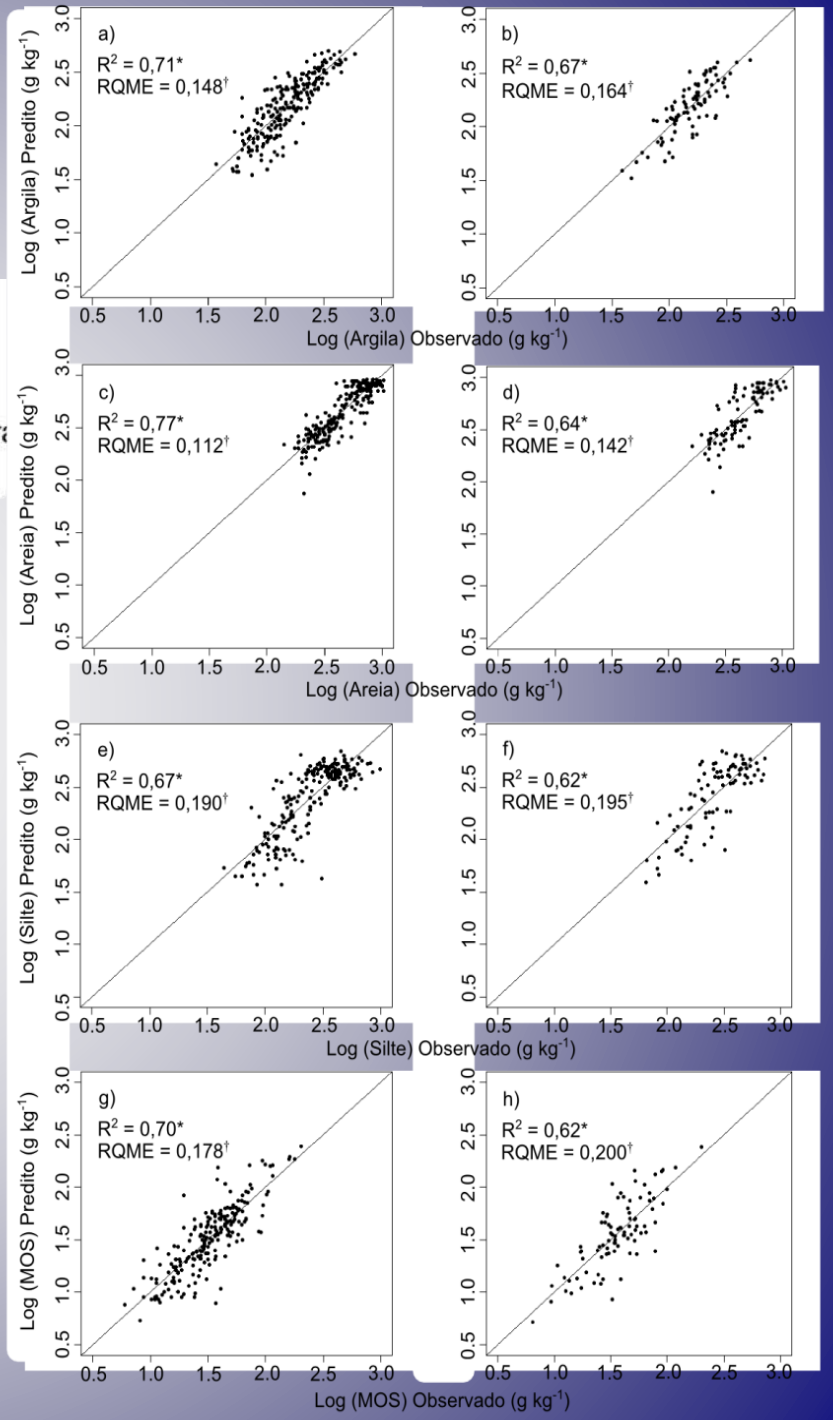
FIGURE 3: Intra-/interlaboratory deviation.

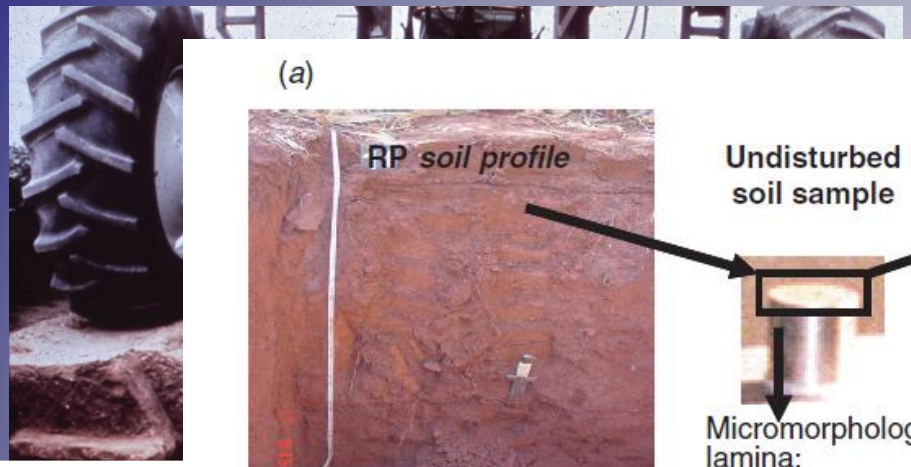
Large variations between laboratories (20% internally), 103% between
Reflectance spectroscopy was found be as good as the commercial laboratories

André Carnieletto Dotto pHD Thesis, 2013, Ricardo Simão Diniz Dalmolin,
Fabrício de Araújo Pedron, Alexandre ten Caten & Luis Fernando Chimelo Ruiz



R^2: 0.70

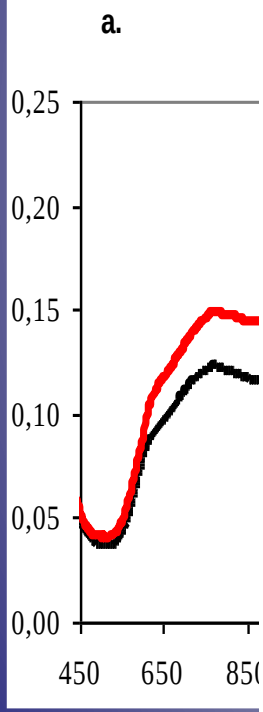




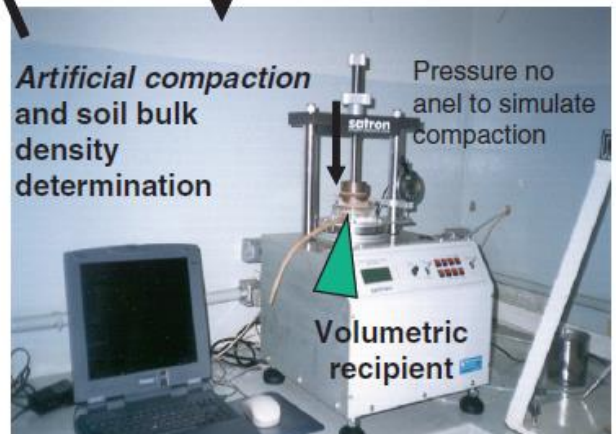
(a)

Undisturbed soil sample

Micromorphology lamina: quantification of pores



Reflectance Factor



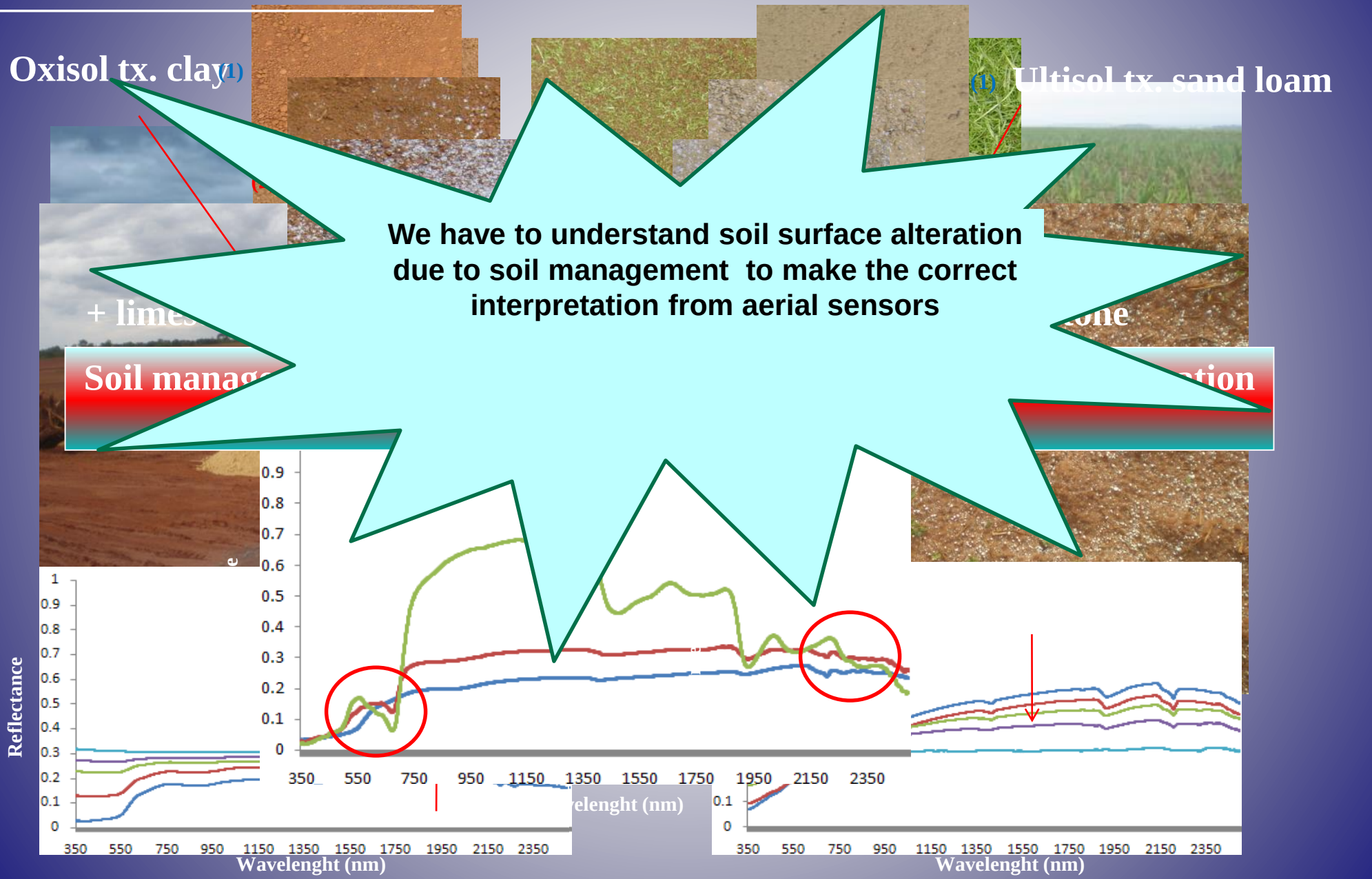
Soil density evaluated by spectral reflectance as an evidence of compaction effects

International Journal of Remote Sensing
Vol. 31, No. 2, 20 January 2010, 403–422

J. A. M. DEMATTÊ†, M. R. NANNI*‡, A. P. DA SILVA†,
J. F. DE MELO FILHO§, W. C. DOS SANTOS¶ and R. C. CAMPOS|

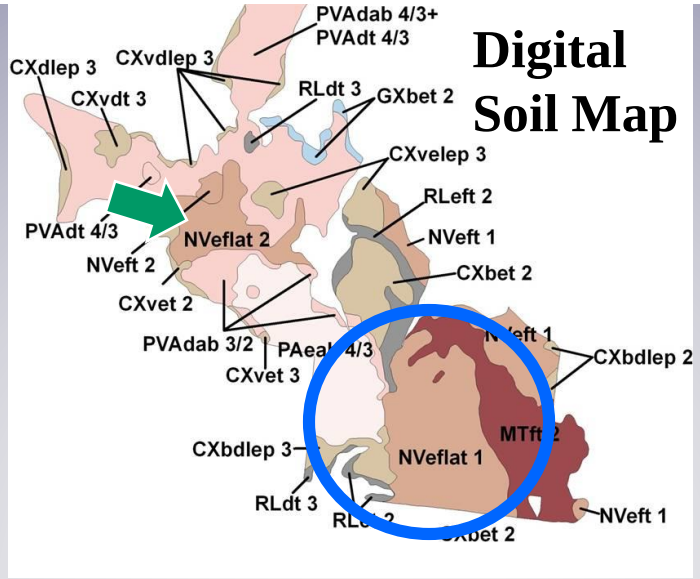
Assessment of sugarcane harvesting residue effects on the soil spectral behavior

J.A.M. Demattê, Bortolleto, M., R. Otto, F.S. Terra, A.F. Nascimento, L.H. Perei, R.S. Toma. (In **in submission** -International Journal of Remote Sensing,2014)



Sequence of works to reach the main goal: soil mapping

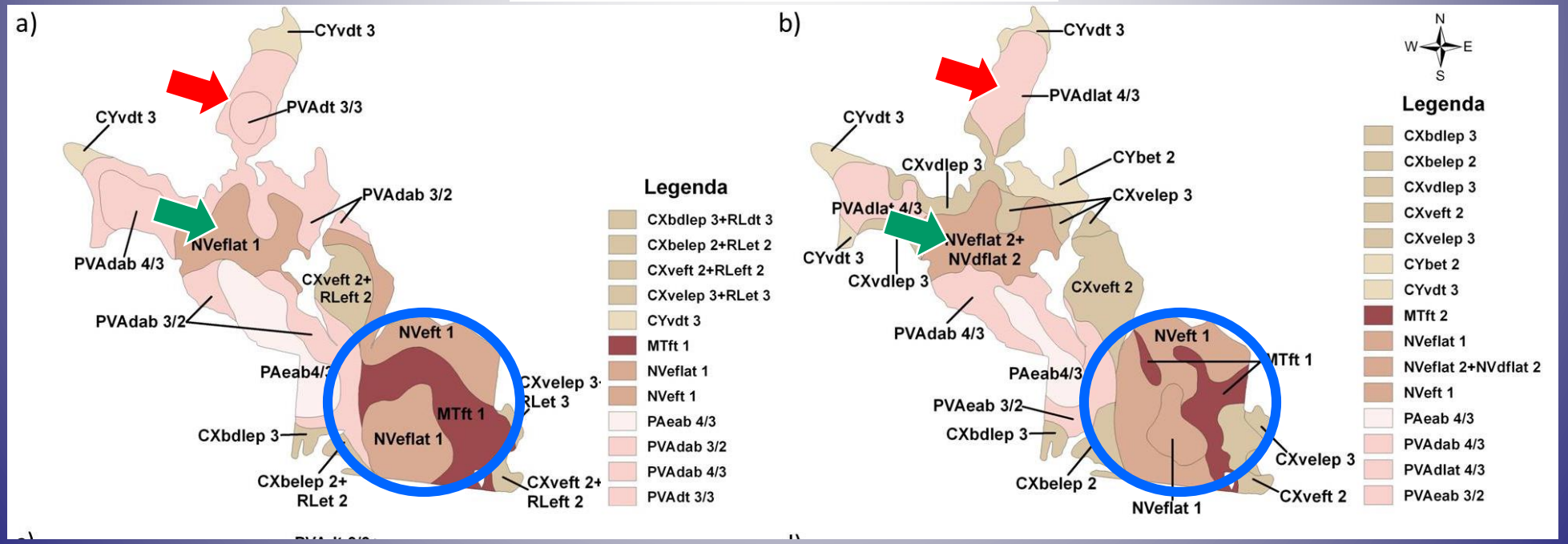
Map from Pedologist A



Digital Soil Map

Diminushe subjectivity: Strategies by soil spectroscopy

Map from Pedologist B



O.Bazaglia, J.A.M.Demattê, I.F.Lepsch,H. Prado, J.A.Mazza (2014-in press Brazilian Journal of Soil Science)

Reflectance spectroscopy of soils post-heating—Assessing thermal alterations in soil minerals

The sensitivity of RS is higher than that of XRD.

RS identifies dehydroxylation of clay minerals at ~400 °C, whereas XRD at ~800 °C

XRD could not identify calcium hydroxide in the heated sample with low calcite concentration, whereas the RS-PTA could.