Soil Spectroscopy: the present and future of Soil Monitoring

FAO HQ, Rome, Italy, 4-6 December 2013

The use of spectral libraries to reduce the influence of soil moisture on the estimation of soil properties from satellite imaging spectroscopy

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Introduction – *estimation of soil variables*

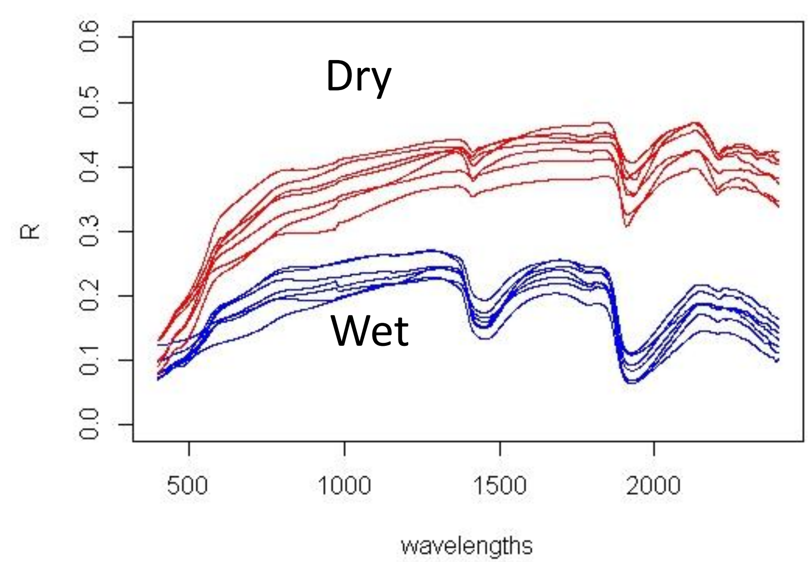
Satellite imaging spectroscopy

Multivariate or hybrid techniques (e.g. PLSR or RK)

Hyperspectral indices

Some obstacles : *spectral resolution, signal quality, geometric and atmospheric correction, availability of bare soil image, roughness, soil moisture….*

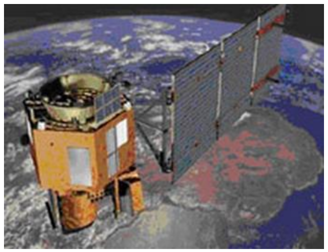
Soil Moisture
generally reduces the reflectance over the entire spectrum, but this decrease is not linear and its magnitude varies depending on the spectral region and the soil type.



Introduction – *hyperspectral remote sensors*

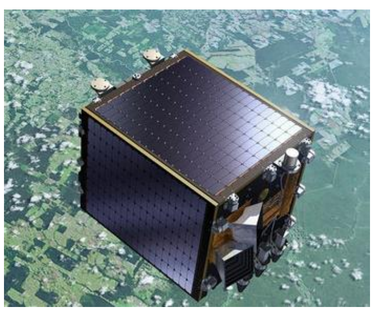
Current

NASA's EO-1: Hyperion



Spectral range 400-2400 nm
220 bands
Spectral resolution 10 nm
Spatial resolution: 30 m

ESA's PROBA: CHRIS

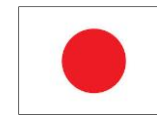


410–1050 nm
Spatial resolution: 18-36 m
From 19 to 63 bands

Future

2016 EnMAP (DLR)

2017 HISUI (METI-JAXA)



2017 PRISMA (ASI)

2021 HyspIRI (NASA)

Aim of the study

The potential of spectral libraries to reduce the influence of soil moisture on the estimation of soil properties from satellite imaging spectroscopy

Calibration of SOC, clay, moisture indices using spectral libraries

Dry

Soil samples characteristics

Different SM levels

Satellite data
(Hyperion and simulated PRISMA data)

Simulated satellite data – PRISMA

Spectra resampling according PRISMA sensor's characteristics (bands, FWHM, expected NEDR)

1. **At-sensor radiance, inverse process of atmospheric correction**

$$Rad(\lambda) = \frac{\rho(\lambda)\tau_{\uparrow}(\lambda)[E_0(\lambda)Cos(\theta_z)\tau_{\downarrow}(\lambda)+E_{\downarrow}(\lambda)]+\pi L_{\uparrow}(\lambda)}{\pi}$$

$Rad(\lambda)$: at-sensor radiance; $\rho(\lambda)$: reflectance; $\tau(\lambda)$: soil transmittance of the sensor; $E_0(\lambda)$: solar spectral irradiance (TOA); θ_z: Solar Zenith Angle; $L_{\uparrow}(\lambda)$: upwelling radiance

2. **Re-obtain reflectance + noise equivalent differential reflectance**

$$Rad(\lambda)_{noisy} = Rad(\lambda) + Gauss(0, NEDR)$$

3. **Atmospheric correction (MODTRAN4)**

$$\rho(\lambda)_{PRISMA} = \frac{\pi[Rad(\lambda)_{noisy} - \pi L_{\uparrow}(\lambda)]}{\tau_{\uparrow}(\lambda)[E_0(\lambda)Cos(\theta_z)\tau_{\downarrow}(\lambda)+E_{\downarrow}(\lambda)]}$$

Spectral libraries

Name	N° samples	Type	Area	Used Soil variable	Variable Range	Moisture	Spectral meas.	Spectral range	Spectral res.
MAC	72	Topsoil	Local	clay	22 - 56 %	4 levels	Directional	350:2500	1 nm
INRA SOLREFLIU	89	Topsoil	World	SOC	0.02 - 6.8 %	4 levels	Directional	350:2500	1 nm
ICRAF-ISRIC	4.437	785 profiles	World	SOC	0 – 58 %	dry	Diffuse	350:2500	10 nm
LUCAS (JRC)	19.967	Topsoil	Europe	SOC, clay	0.1 – 16 (SOC) 3 – 78 (clay)	dry	Diffuse	400-2499.5 nm	0.5 nm

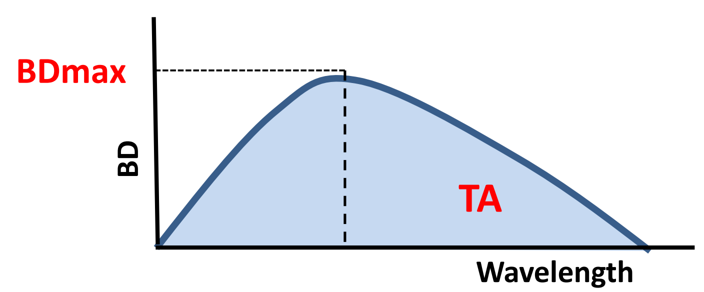
Spectral libraries - Methodology

1. **Transformation of all spectra from reflectance (R) to Band depth (BD) and absorbance (A)**

2. **Correlation analysis between A, BD, R and soil variables for all wavelengths**

3. **Detection of spectral ranges having high correlation values**

4. **Mean and maximum BD value and total area of the most promising spectral ranges were used to develop simple or normalized ratio indices.**



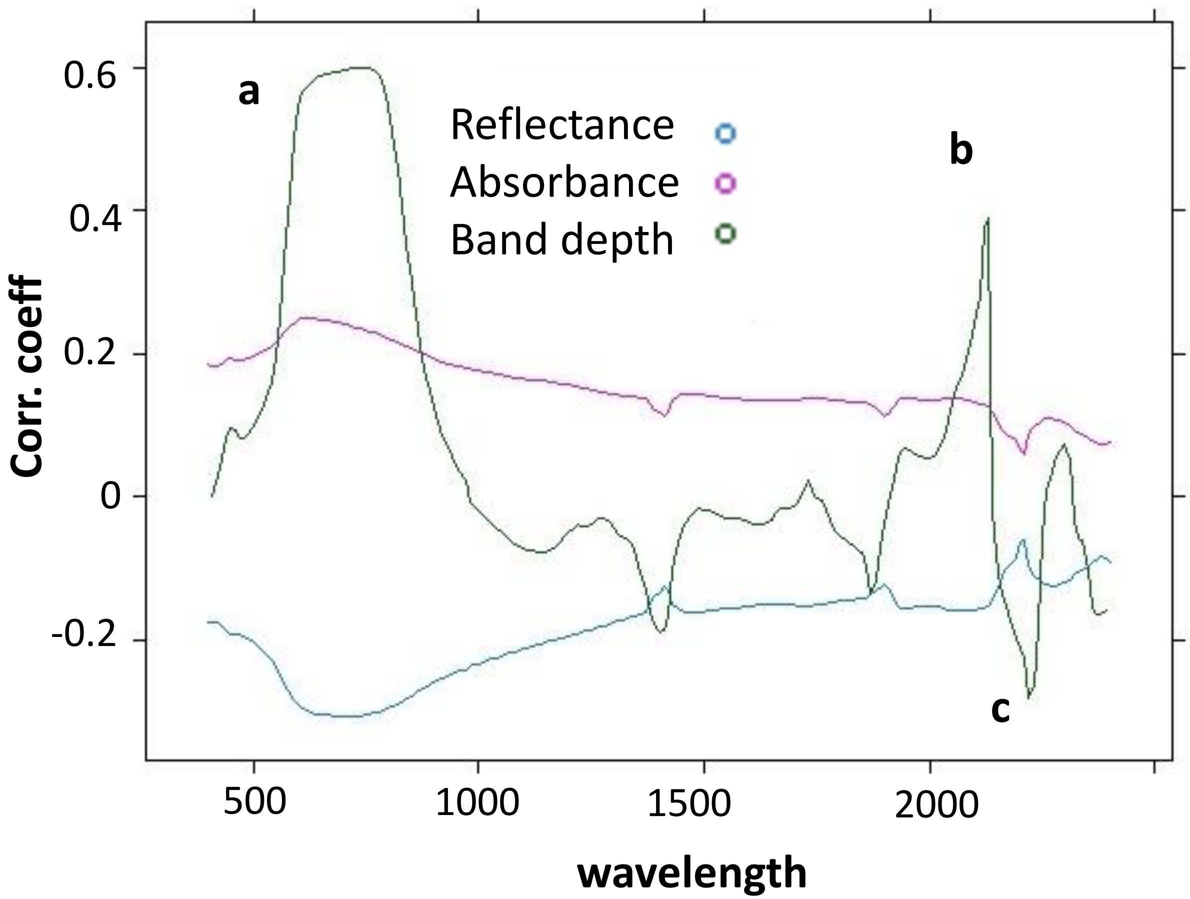
5. **The indices were correlated with soil variables, using two-thirds of datasets for calibration one third for validation (RMSE and RPD)**

Preliminary survey – ICRAF-ISRIC, SOC

631 samples 0 – 30 cm

a=640:790
b=2110:2130
c=2210:2230

BDmax_b/BDmax_c **ρ = 0.9**



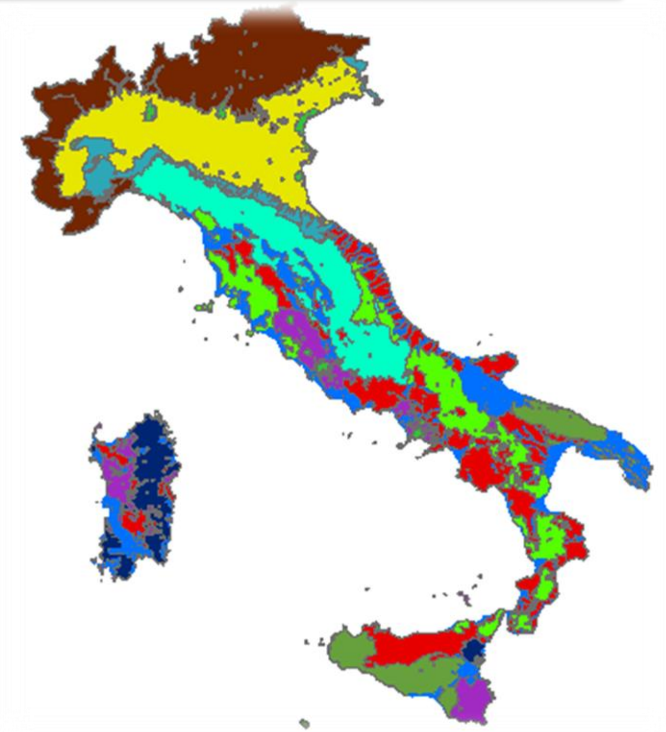
Index
RMSE= 1.4
RPD= 2.5

PLSR
RMSE= 1.5
RPD= 2.3

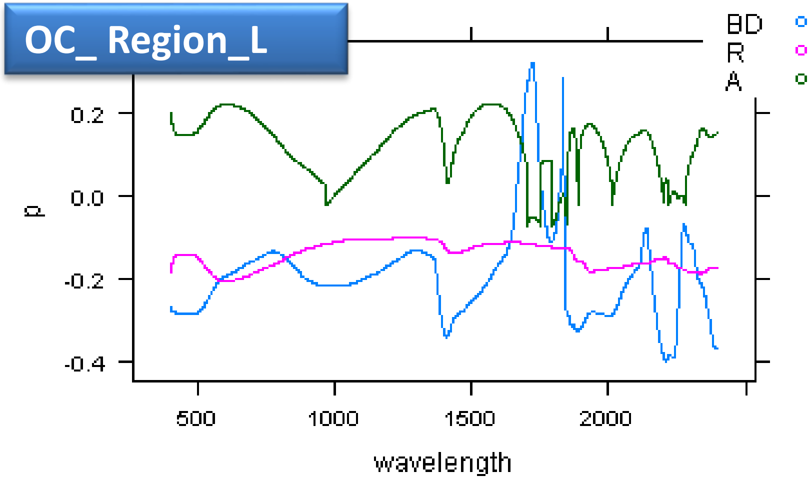
Preliminary survey – LUCAS, SOC and Clay

Extraction of soil samples and spectral measurements on cropland areas of Italy ~1200 samples

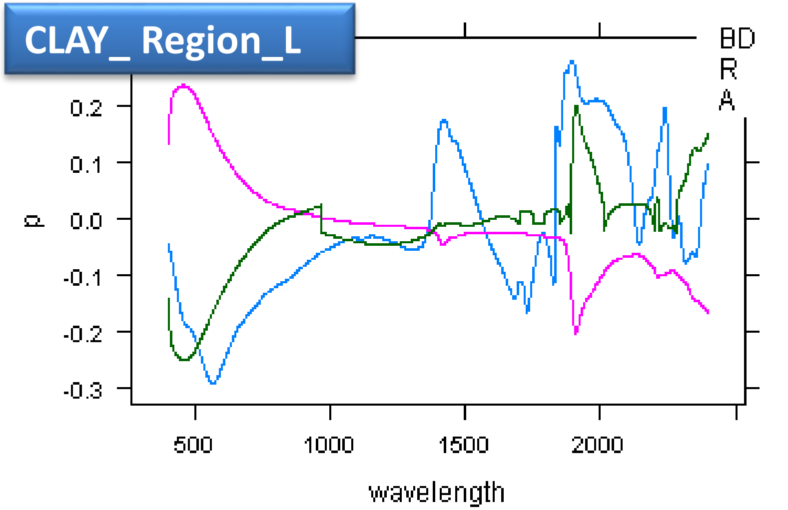
Split samples by Soil Region of Soil Map of Italy



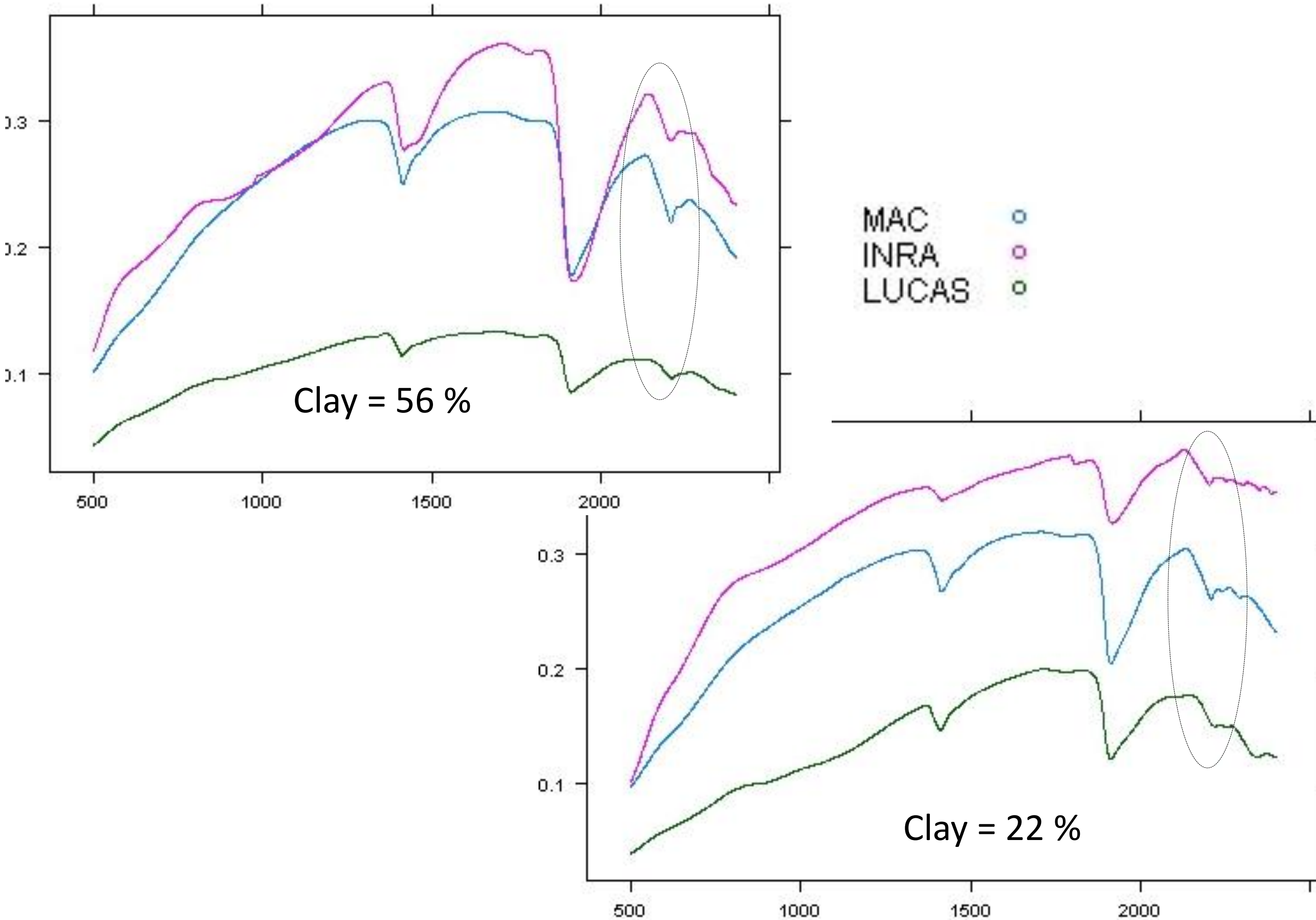
OC_ Region_L



CLAY_ Region_L



Preliminary survey – LUCAS, Clay



Preliminary survey – LUCAS, SOC and Clay

Region L: Soils of the plains and low hills of central and southern Italy
(Cambisol,Luvisol,Calcisol,Regosol,Vertisol)

98 samples

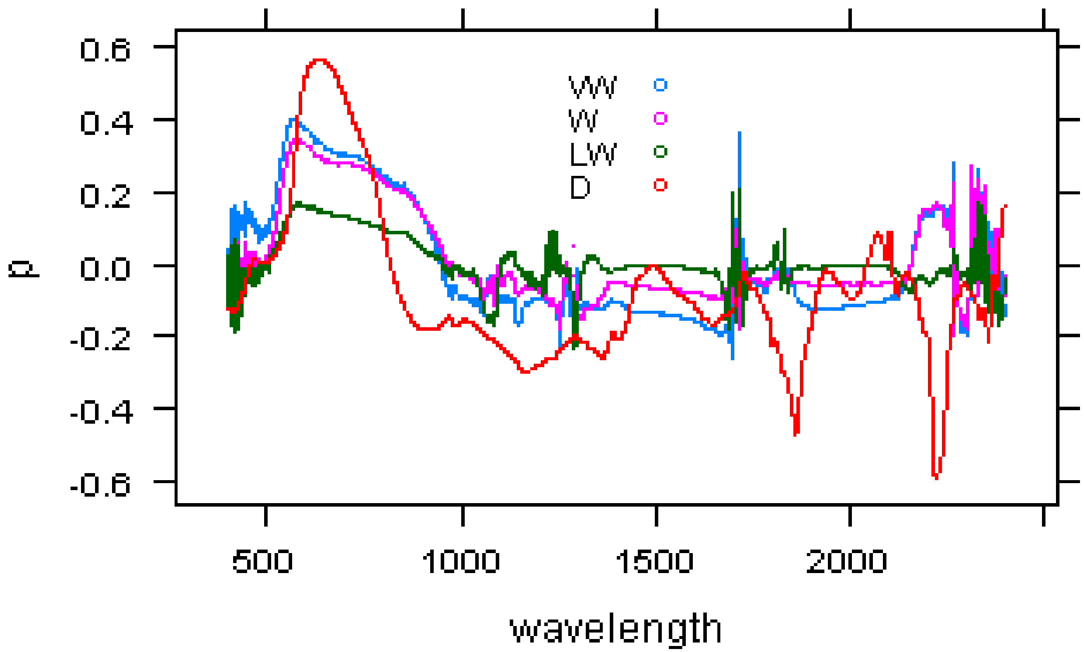
PLSR	RMSE	RPD
SOC	0.6	1.4
Clay	7.0	1.6

Region D: Soils of the Po plain and associated hills
(Cambisol,Luvisol,Calcisol,Fluvisol,Vertisol)

243 samples

PLSR	RMSE	RPD
SOC	0.7	1.9
Clay	7.0	1.7

Preliminary survey – INRA, SOC



Index	RMSE	RPD
VW	1.2	1.2
W	1.2	1.1
LW	1.2	1.2
D	1.1	1.3
Mean	**1.2**	**1.2**
Dry to all	**1.2**	**1.2**

PLSR	RMSE	RPD
VW	0.7	2.0
W	0.8	1.9
LW	0.7	2..0
D	1.0	1.5
Mean	**0.8**	**1.8**
Dry to all	**3.3**	**0.7**

Soil moisture	Abb	range	index	Pearson's coeff. (ρ)
Very Wet	VW	0.62 – 0.81 %	$TA_{620:650}$	0.66
Wet	W	0.34 - 0.61 %	$BDmax_{620:650}$	0.63
Little wet	LW	0.14 – 0.33 %	$BDmax_{620:650}$	0.64
Dry	D	0 – 0.13 %	$(BDm_{620:650}-BDm_{2210:2240})/(BDm_{620:650}+BDm_{2210:2240})$	0.63

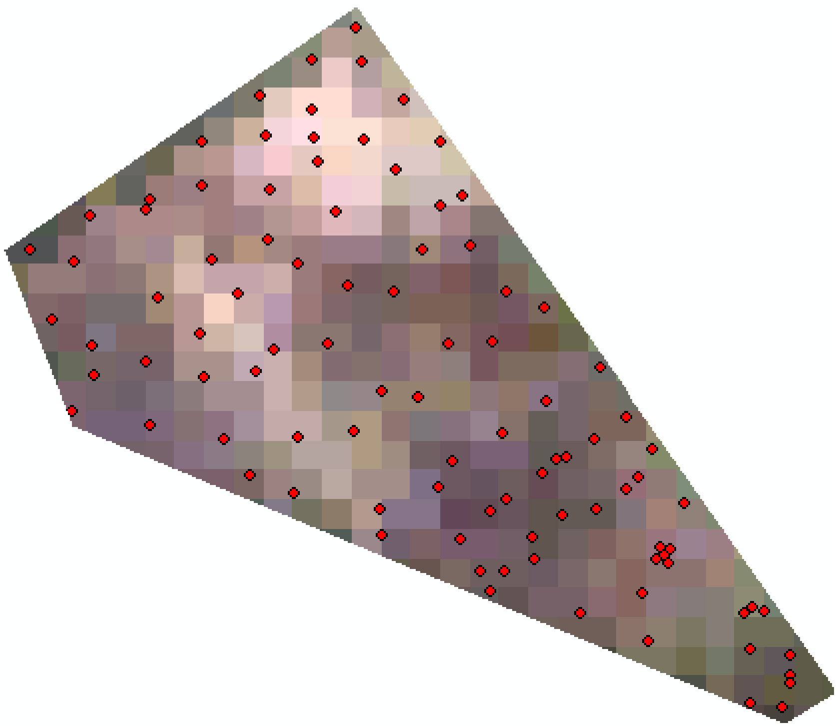
Satellite data – EO-1 Hyperion, SOC

B041 Field (26 ha) in Maccarese S.p.a (Central Italy)

97 SOIL SAMPLES: texture (%), and SOC (%)

Clay: 18 - 50 %

SOC: 0.6 to 1.4 %



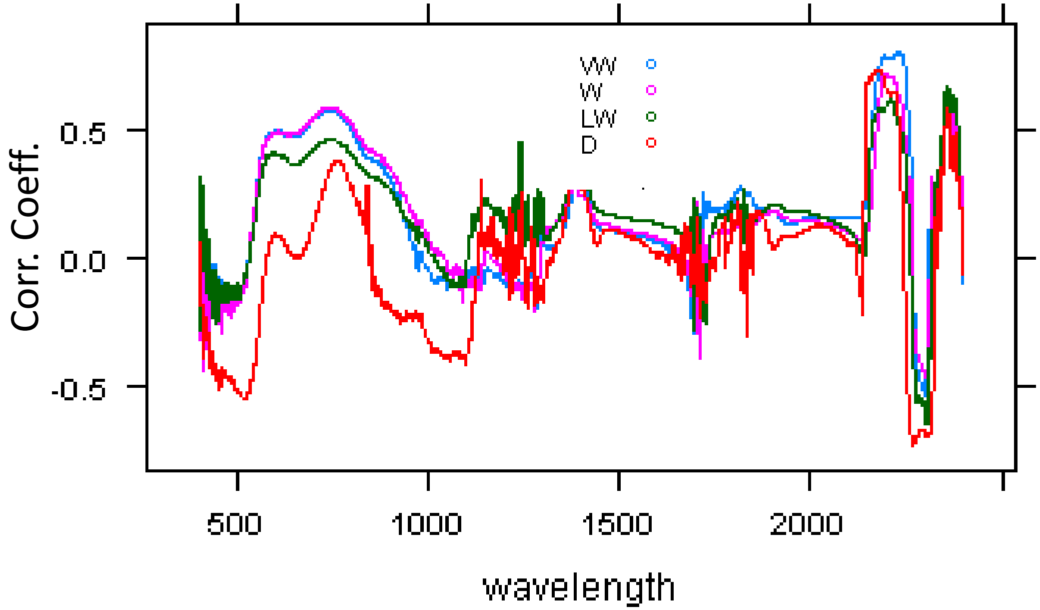
Index

Library	RMSE
INRA	0.4
ICRAF-ISRIC	0.4
LUCAS (Region L)	0.6

PLSR

	RMSE	RPD
SOC	0.23	1.15

Preliminary survey – MAC, Clay

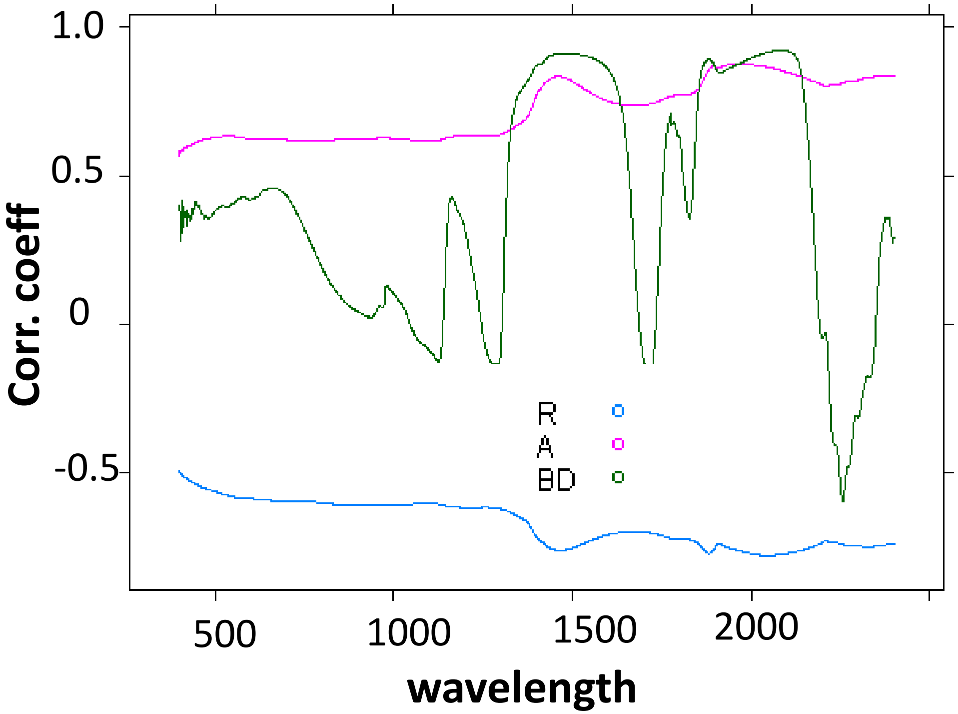


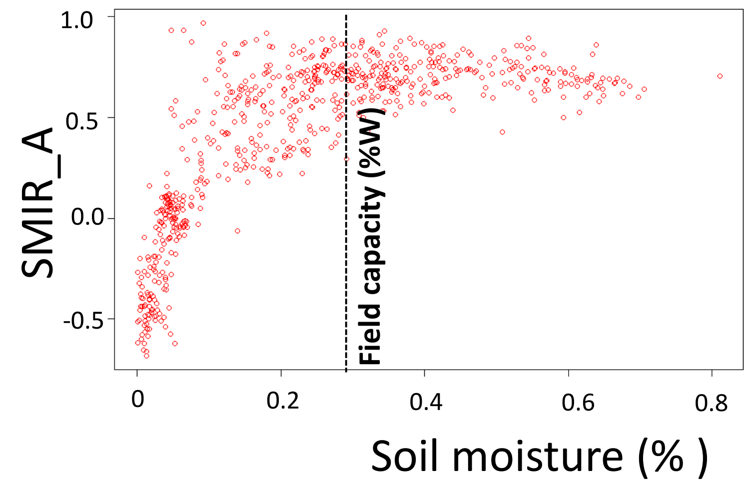
Index	RMSE	RPD
VW	4.4	2.0
W	6.4	1.4
LW	6.3	1.4
D	5.8	1.5
Mean	**5.7**	**1.6**
Dry to all	**8.2**	**1.1**

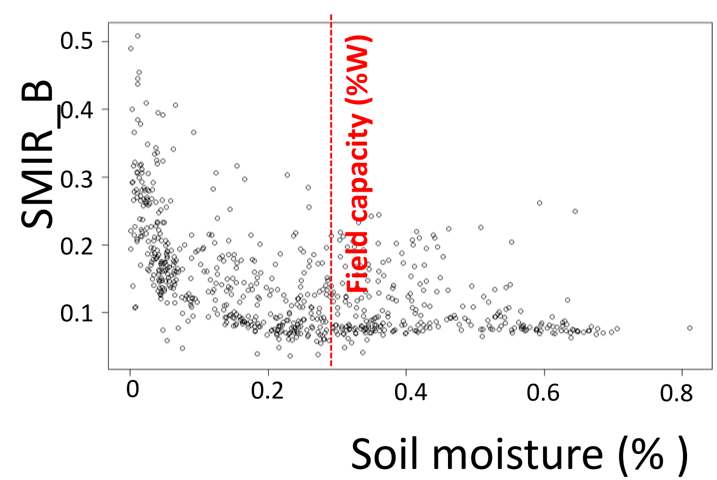
Soil moisture	Abb	range	index	Pearson's coeff. (ρ)
Very Wet	VW	**0.43 – 0.7 %**	$\mathbf{BDm_{2180:2250}}$	0.79
Wet	W	**0.29- 0.42 %**	$\mathbf{BDm_{2180:2220}}$	0.71
Little wet	LW	**0.08 – 0.28 %**	$\mathbf{(BDm_{2340:2360}-BDm_{1230\text{-}1240})/(BDm_{2340:2360}+BDm_{1230\text{-}1240})}$	0.70
Dry	D	**0 – 0.07 %**	$\mathbf{(BDm_{2140:2190}-BDm_{2260:2300})/(BDm_{2140:2190}+BDm_{2260:2300})}$	0.76

PLSR	RMSE	RPD
VW	3.9	2.2
W	5.0	1.7
LW	6.4	1.4
D	4.7	1.8
Mean	**5.1**	**1.7**
Dry to all	**15.7**	**0.5**

Preliminary survey – SMIR, MAC + INRA







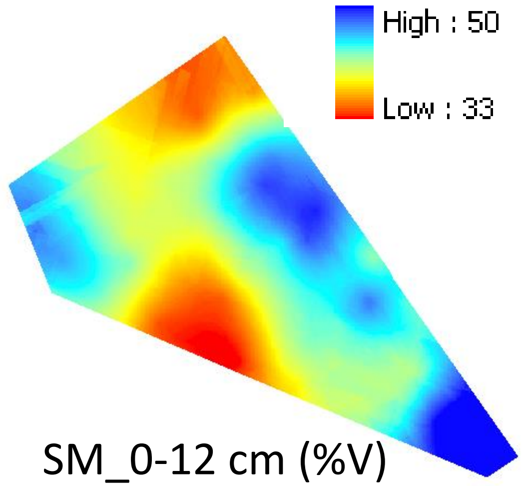
Soil Moisture Index (SMIR)

A - $(BD_{2088}-BD_{2253})/(BD_{2088}+BD_{2253})$ $\rho=0.73$
B - $(R_{671}-R_{559})/(R_{671}+R_{559})+R_{1638}$ $\rho=-0.64$

Satellite data – SMIR

EO-1 Hyperion bare soil Image 7th November 2012

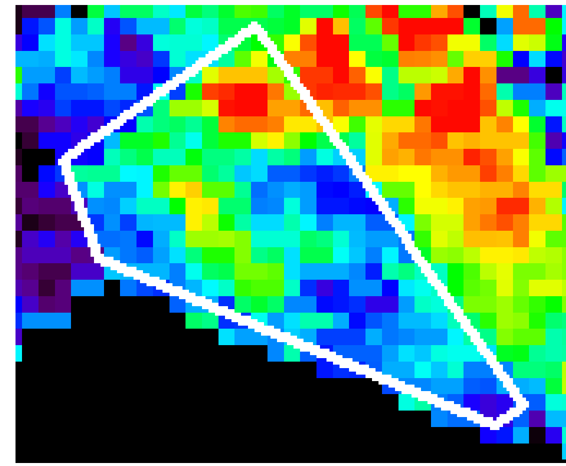
Field sampling – TDR 8th November 2012

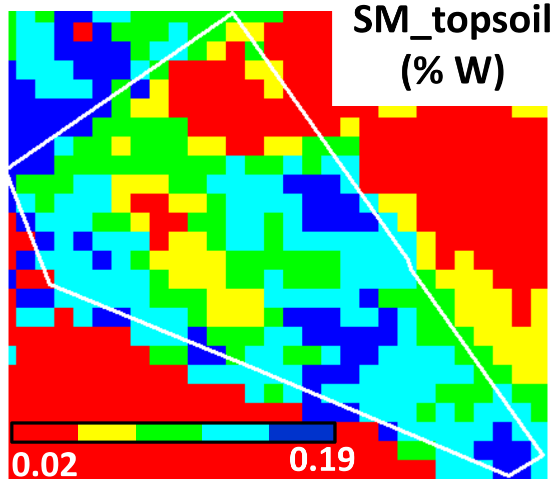


SM_0-12 cm (%V)

SMIR_B

$(R_{671} - R_{559})/(R_{671} + R_{559})\ R_{1638}$

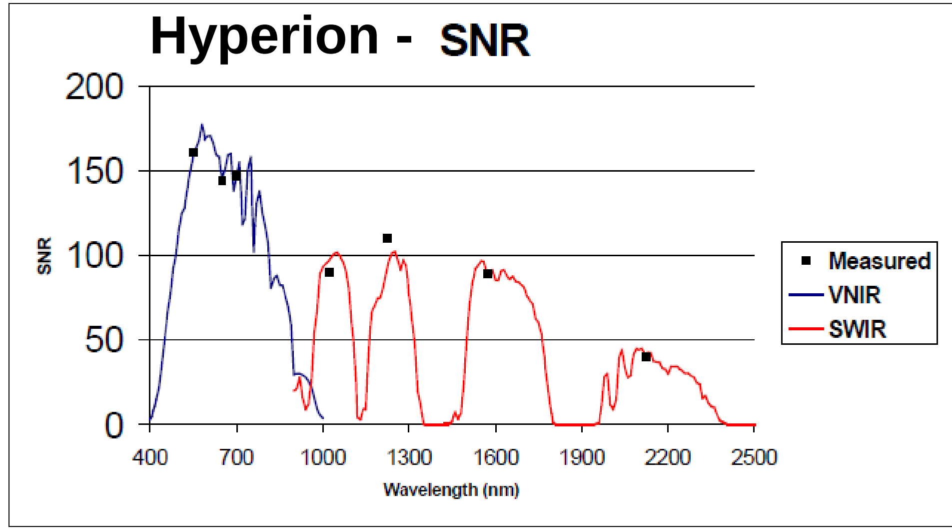




SM_topsoil (% W)

Satellite data – EO-1 Hyperion, CLAY

The best clay indices mainly use SWIR between 2200 and 2400 nm

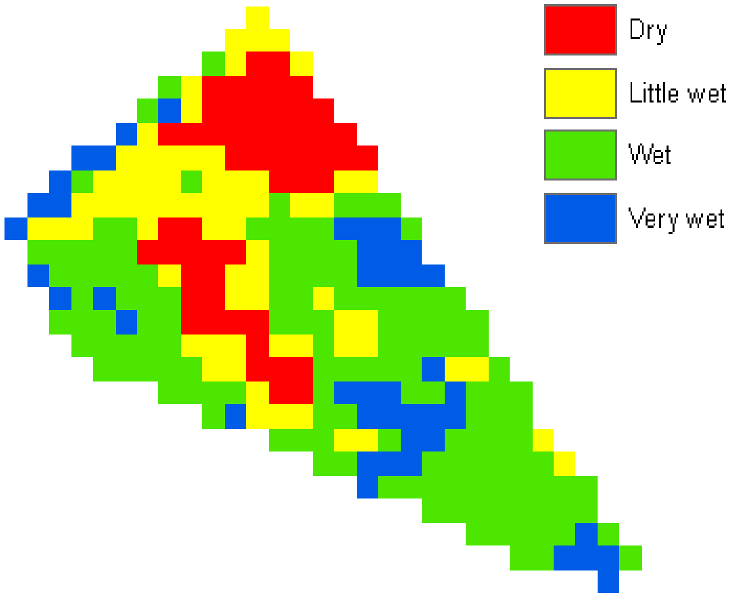


We had to employ indices that use only VIS /NIR data, though these showed worse validation performances on the MAC dataset.

MAC	Correlation coefficient (validation results on MAC)	
	Best Lab index	Hyperion index
Dry	0.76	0.76
Little wet	0.70	0.30
Wet	0.71	0.58
Very wet	0.79	0.57

Satellite data – EO-1 Hyperion, CLAY

Different indices according to SM classes



RMSE=10 %

Dry index to all field

RMSE=14 %

Simulated satellite data– PRISMA

SOC		Summer	Autumn	Winter		Full spectrum
ICRAF-ISRIC	RMSE	1.5	1.5	1.9		1.4
	RPD	2.16	2.15	1.76		2.5
INRA	RMSE	1.1	1.1	1.0		1.1
	RPD	1.32	1.31	1.35		1.31

MAC

Different indices according to SM - RMSE

CLAY	summer	autumn	winter	lab
D	5.9	6	5.9	5.8
LW	13	9.4	9.9	6.3
W	8.2	8.5	10.6	6.4
VW	6.6	6.3	6.3	4.4
Mean	8.4	7.6	8.2	**6.4**

Dry index to all - RMSE

CLAY	summer	autumn	winter
D	5.9	6	5.9
LW	11	11.5	11.1
W	16.9	16.6	11.5
VW	19.1	19.2	19.2
Mean	13.2	13.3	11.9

Conclusions

Spectral libraries

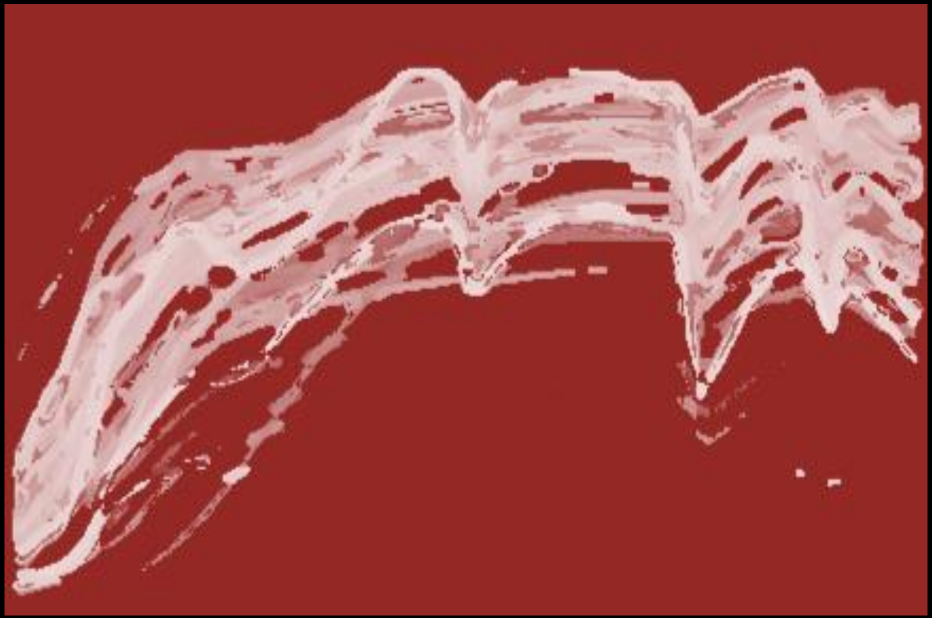
- ***Using some libraries we obtained indices having validation results higher or equal than PLSR models (ICRAF-ISRIC, MAC)***
- ***The tests performed on MAC data show how the spectral features related to clay are affected by soil moisture***

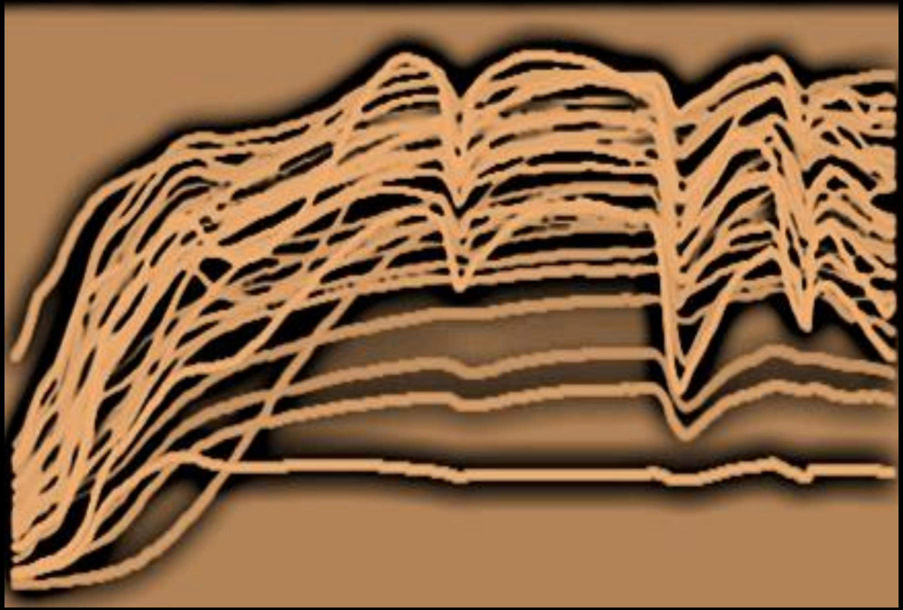
Remote data

- ***The SMIR_B allowed to delineate variable soil moisture areas using Hyperion image***
- ***Simulated PRISMA's data highlighted the importance of a priori knowledge of soil moisture for clay estimation.***

Future applications

- ***A synergy with satellite radar data (COSMO SkyMed) could be also envisaged to improve the SM estimation.***
- ***The coming hyperspectral sensors should have a better signal quality than Hyperion, hopefully opening the way for the routine estimation of topsoil properties from bare soil images.***
- ***Spectral measurements at different moisture levels are desirable in large spectral libraries to calibrate indices according to soil moisture content***





Thank you for your attention