

PRISMA Workshop

“PRISMA mission - hyperspectral national missions pioneer - data exploitation”,
ASI Headquarters, Rome, 1-3 March, 2017

Potential of the PRISMA mission for estimating topsoil properties and surface contaminants

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S A P 4 P R I S M A project (ASI)

Development of algorithms and products for applications in agriculture and land monitoring
to support the PRISMA mission



1. Topsoil properties estimation by regression analysis and indexes
 - Soil texture (clay and sand content) and Soil Organic Matter (SOM) in the first 30 cm of agricultural soils
 - Examples of estimation maps of soil texture and SOM
 - Calibration/Validation of the methodologies and products
2. Identification and monitoring of surface pollutants through specific spectral features
 - Analysis and optimization of methods and algorithms for the estimation of soil/water pollution due to human activities and natural hazards according to the PRISMA sensors' characteristics
 - Distribution maps of pollutants
 - Calibration/Validation of the methodologies and products

Soil texture estimation rationale

Precision agricultural management takes into account the variability in soil properties and allows a more efficient use of resources such as water and fertilisers



The availability of detailed information on soil properties at the field scale is crucial



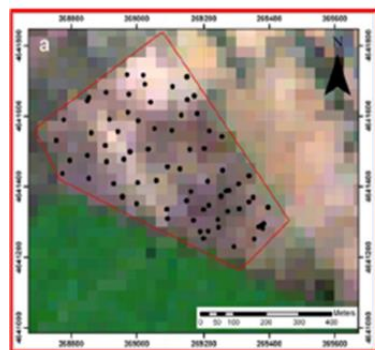
Excessive cost of spatially dense soil sampling and analysis

There is great interest in the development of low cost soil mapping methods such as satellite or airborne remote sensing



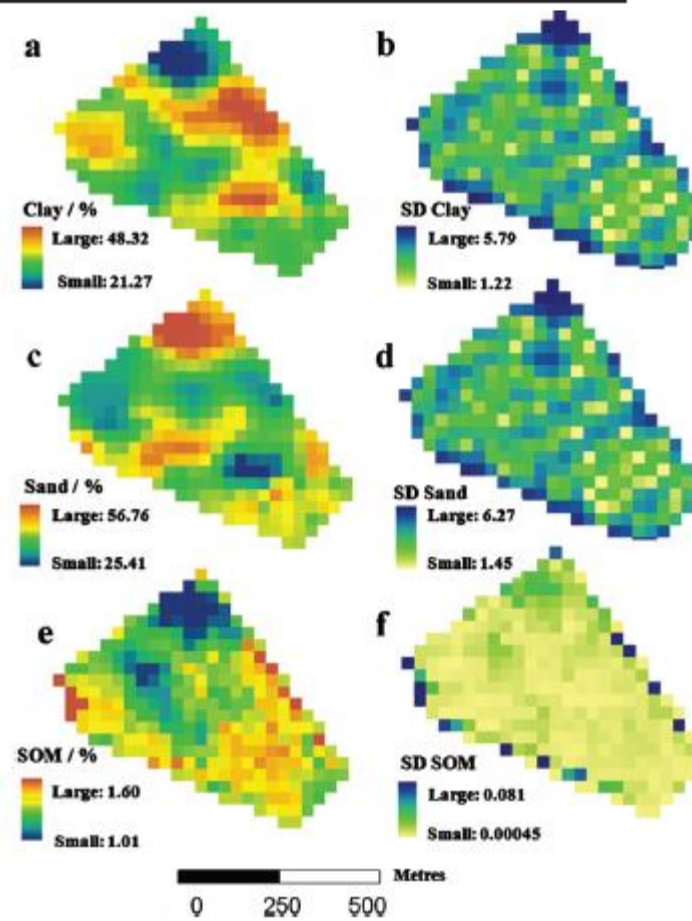
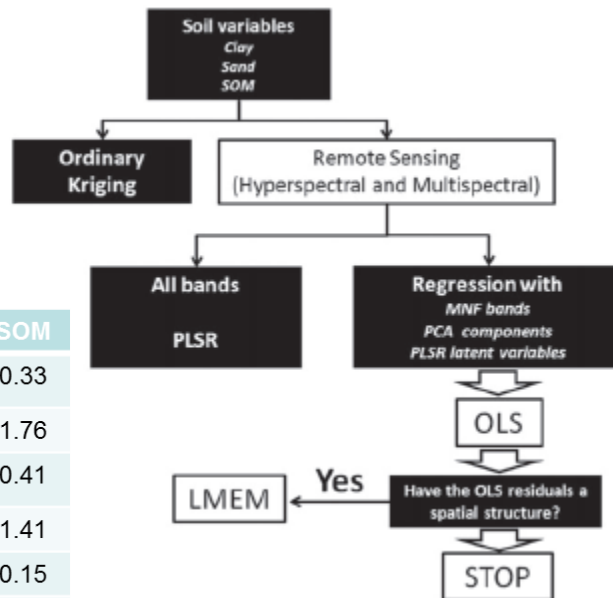
Imaging spectroscopy of bare soils has been shown to have considerable potential for the estimation of properties such as **soil texture**

Soil texture estimation: results on Maccarese farm (Rome)



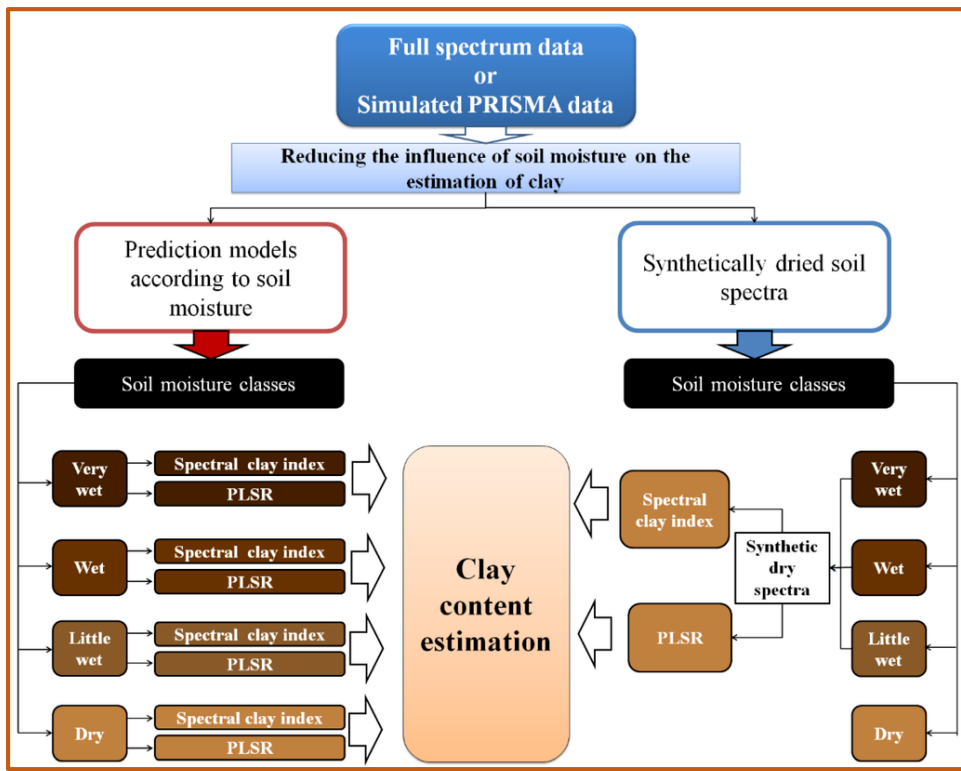
Field	Variable	n	Min / %	Max / %	Mean / %	σ	CV	Skewness
B041	Clay	72	18.37	49.61	37.91	6.82	0.18	-0.37
	Sand	72	23.10	60.43	36.55	7.31	0.20	0.95
	SOM	72	1.07	2.67	1.69	0.44	0.26	0.64

		Clay	Sand	SOM
OK Ordinary K.	RMSE	4.46	5.18	0.33
	RPIQ	2.29	1.69	1.76
PLSR Partial least square regr.	RMSE	5.95	6.69	0.41
	RPIQ	1.64	1.31	1.41
LMEM Linear mixed effect model	RMSE	4.07	4.90	0.15
	RPIQ	2.40	1.79	3.87

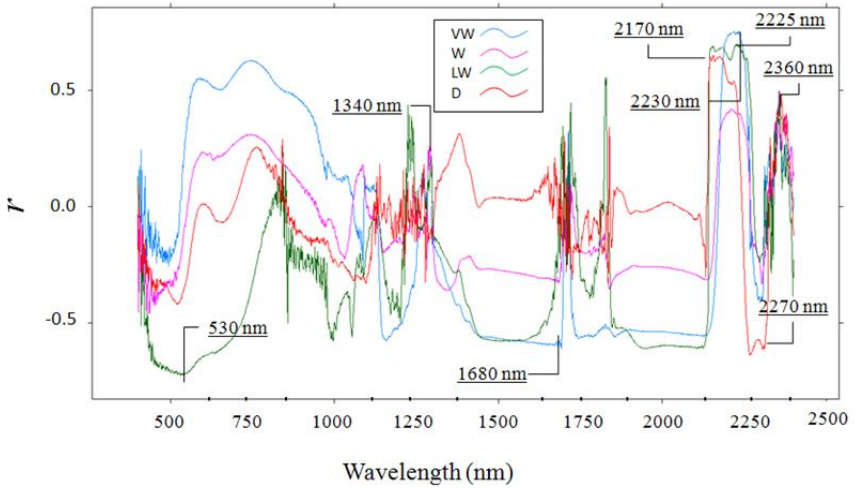


F. Castaldi, R. Casa, A. Castrignanò, S. Pascucci, A. Palombo and S. Pignatti. *Estimation of soil properties at the field scale from satellite data: a comparison between spatial and non-spatial techniques*, *European Journal of Soil Science*, Volume 65, Issue 6, pages 842–851, November 2014.

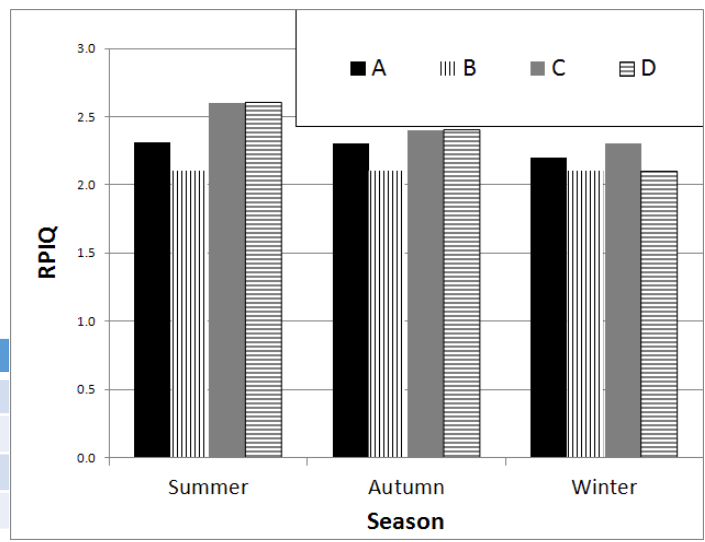
Soil Moisture (SM) to improve the estimation of clay: PRISMA-simulated spectra using spectral libraries



SM class	Clay index	r
VW	$(BD_{2230} - BD_{1680}) / (BD_{2230} + BD_{1680})$	0.70
W	$(BD_{1340} - BD_{2360}) / (BD_{1340} + BD_{2360})$	-0.73
LW	BD_{530} / BD_{2225}	0.65
D	$(BD_{2170} - BD_{2270}) / (BD_{2170} + BD_{2270})$	0.75



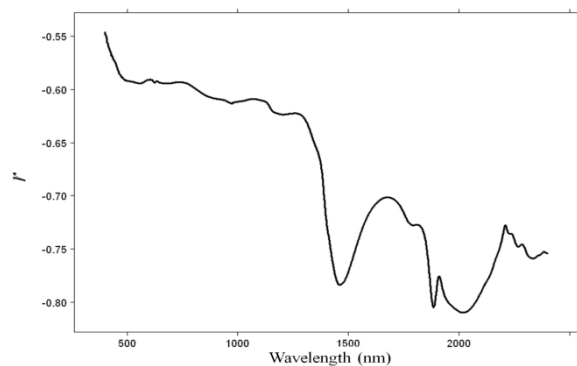
Pearson's correlation coefficient between clay content and Band Depth (BD) spectral values for the four soil moisture classes of the MAC dataset (VW: very wet; W: wet; LW: low wet; D: dry)



Ratio of performance to interquartile range (RPIQ) statistics values obtained for clay estimation using simulated PRISMA data by means of different models according to SM with clay indices (A) and PLSR (C), and synthetically dried spectra both with clay indices (B) and PLSR (D)

The *a priori* knowledge of SM, for the selection the optimal clay index on the basis of the SM class, decreased by 27% the RMSE in retrieving clay content in soils

Soil Moisture (SM) to improve the estimation of clay: results of SM indexes applied to Hyperion dataset

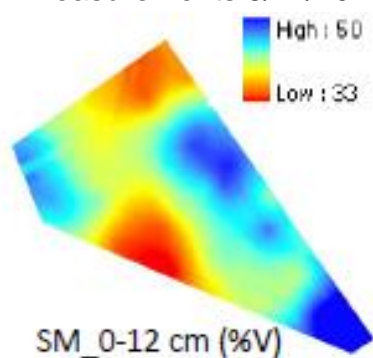


Pearson's correlation coefficient (r) between soil moisture content and reflectance values of MAC and SOLREFLIU spectral datasets as a function of the wavelength

Cross-validation results for Pearson's correlation coefficient (r)
Coefficients results of the quadratic regressions ($SM = a+b*index+c*index^2$),
RMSE and the RPIQ range

Soil Moisture Index	Formula	r	a	b	c	RMSE (%)	RPIQ
SMIR_A	$(R_{1770} - R_{2100}) / (R_{1770} + R_{2100})$	0.89	0.03	1.63	-1.89	0.05	4.25
SMIR_B	R_{1506} / R_{1770}	-0.88	0.48	0.24	-0.75	0.05	4.25
NSMI	$(R_{1800} - R_{2119}) / (R_{1800} + R_{2119})$	0.88	0.50	-1.67	1.46	0.05	4.25

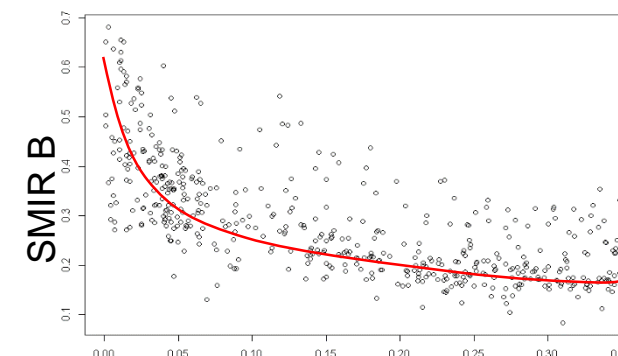
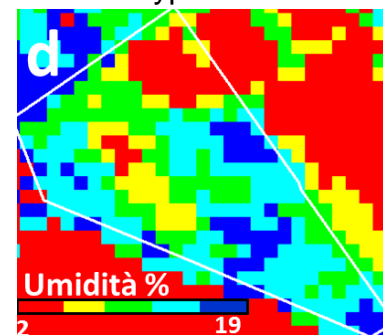
TDR ground measurements 8/11/2012



Hyperion (7/11/2012)

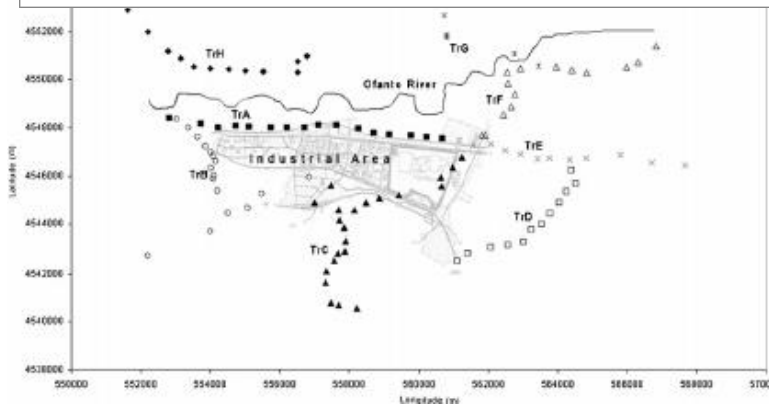
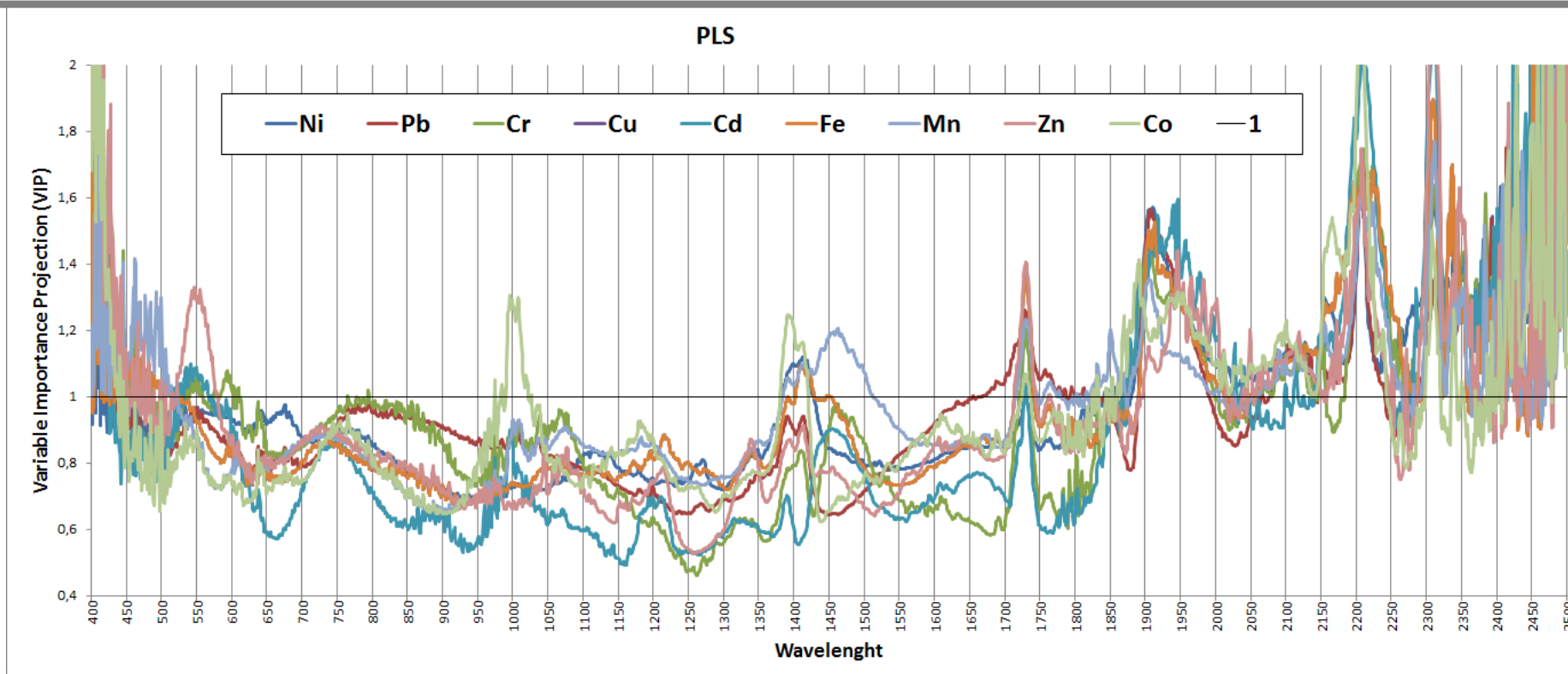


SMIR - B index applied to Hyperion refl.



Castaldi et al., 2015. Reducing the Influence of Soil Moisture on the Estimation of Clay from Hyperspectral Data A Case Study Using Simulated PRISMA Data. *Remote Sens.* **2015**, 7, 15561-15582

Soil contamination - Heavy metals estimation from lab spectra

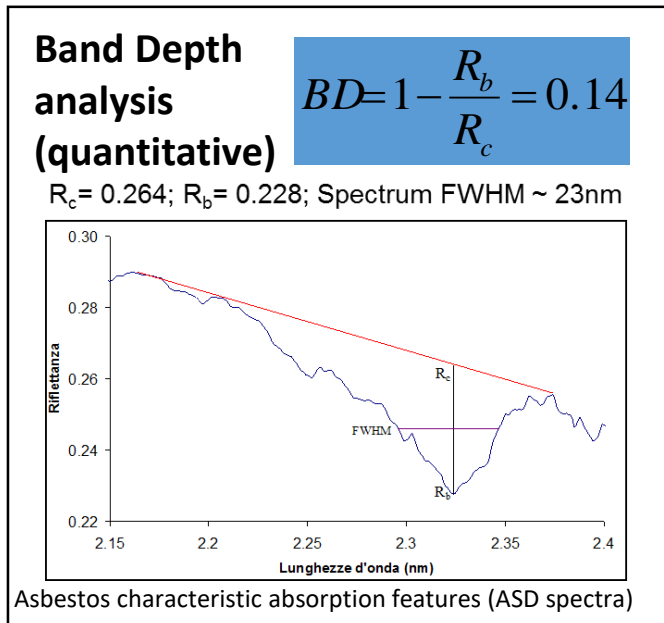


110 soil samples collected in the Melfi industrial area (Basilicata Region) for more than 10 years (1993-2005)

Laboratory XRD and XRF heavy metals concentration & ASD spectral measurements were performed to explore the potential of hyperspectral RS for heavy metals retrieval on soils by PLS Regression analysis

Choe et al., 2008. *Mapping of heavy metal pollution in stream sediments using combined geochemistry, field spectroscopy, and hyperspectral remote sensing: A case study of the Rodalquilar mining area, SE Spain. Remote Sens. Of Environm. 2008*, 112, 3222-3233

Mapping asbestos: spectral feature analysis and detection limit



Hyperion sensor characteristics used for the calculation of the **BDL** (minimum level of the absorption peak depth that an instrument can register):

- SNR @ 2.32 $\mu\text{m} \sim 20$
- Band width @ 2.32 $\mu\text{m} \sim 10 \text{ nm}$

$$BDL(Hyperion) = \frac{CF}{SNR \sqrt{\frac{\text{spectrumFWHM}}{BandWidth}}} = 0.066$$

$$f_{\min}(Hyperion) = \frac{BDL}{BD} = 48\%$$

The main problem encountered in Hyperion images in testing the BD spectral algorithm for the detection of the serpentinite outcrops is due to the Hyperion SNR in the SWIR range, which enables only its detection when the noise of the acquired imagery does not mask the spectral absorption features of interest

PRISMA characteristics used for calculating the BDL:

- SNR @ 2.32 $\mu\text{m} \sim 200$
- Band width @ 2.32 $\mu\text{m} \sim 7.6 \text{ nm}$

$$BDL(PRISMA) = 0.006$$

$$f_{\min}(PRISMA) = 4.3\%$$

Mapping natural asbestos outcrops and secondary deposits: example results on PRISMA-like dataset

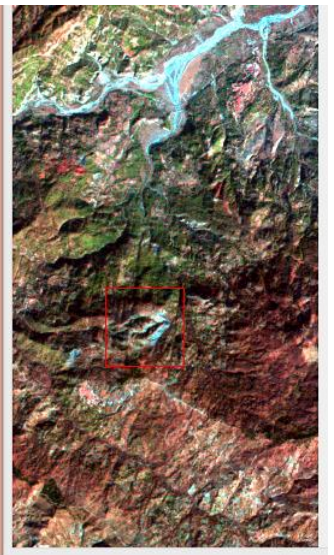
Study site San Severino Lucano (Basilicata): area within the Pollino National Park where natural outcrops and secondary deposits of asbestos-containing rocks (serpentinite) occurs



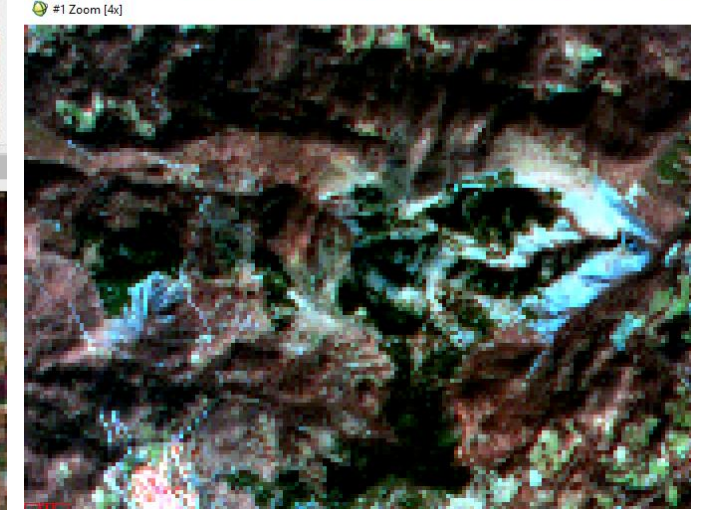
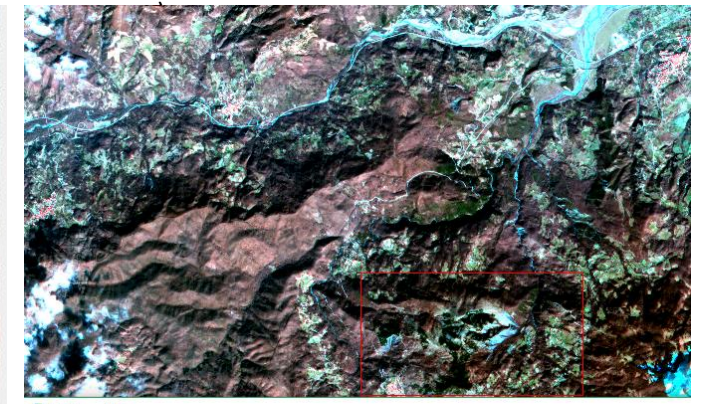
Hyperion (30/8/2012)
R (2324 nm); G (559 nm); B (487 nm)



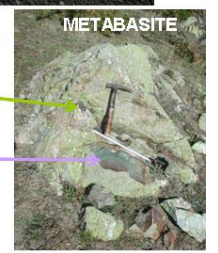
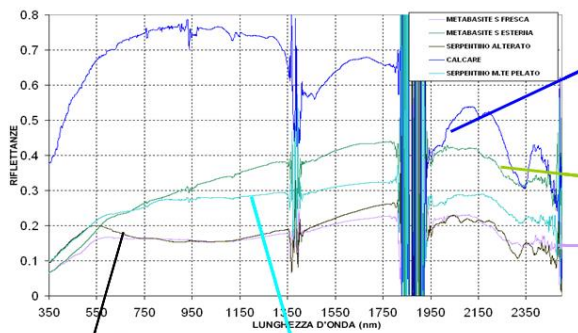
Hyperion (4/12/2001)
R (2324 nm); G (559 nm); B (487 nm)



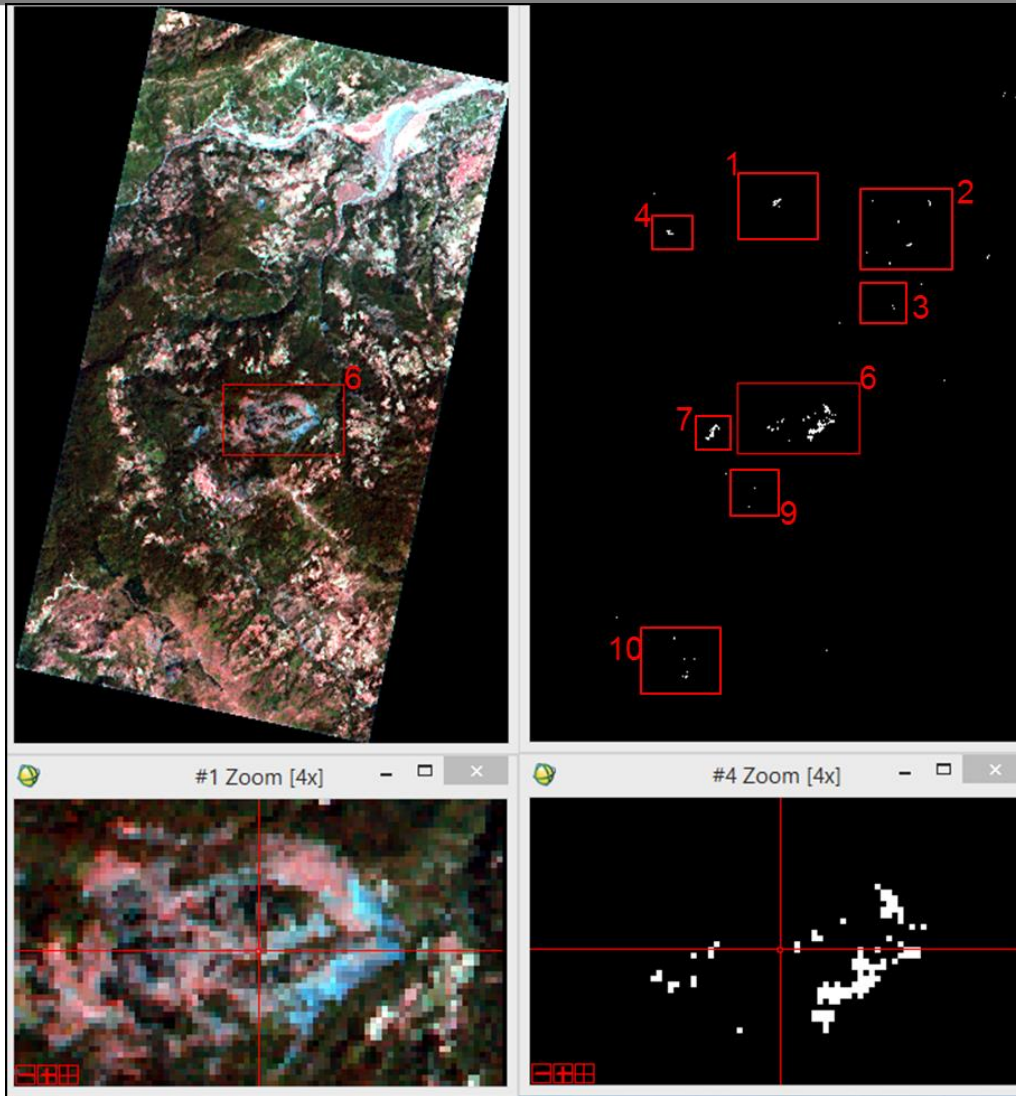
Sentinel 2 (17/02/2017)
R (2190 nm); G (560 nm); B (480)



ASD spectra acquired *in situ*

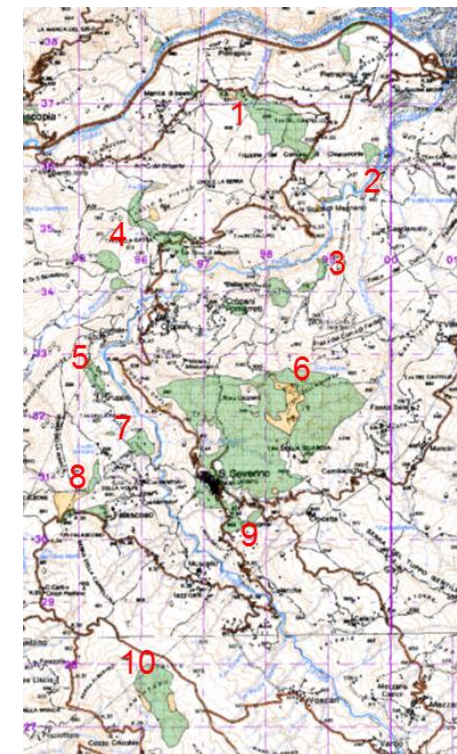


Mapping natural asbestos outcrops and secondary deposits: example results on PRISMA-like dataset



Hyperion (30/8/2012) imagery (R:2324 nm; G:559 nm; B:487 nm)

Serpentinites outcrops map: SFF algorithm applied on Hyperion 2012 geo-corrected reflectance imagery

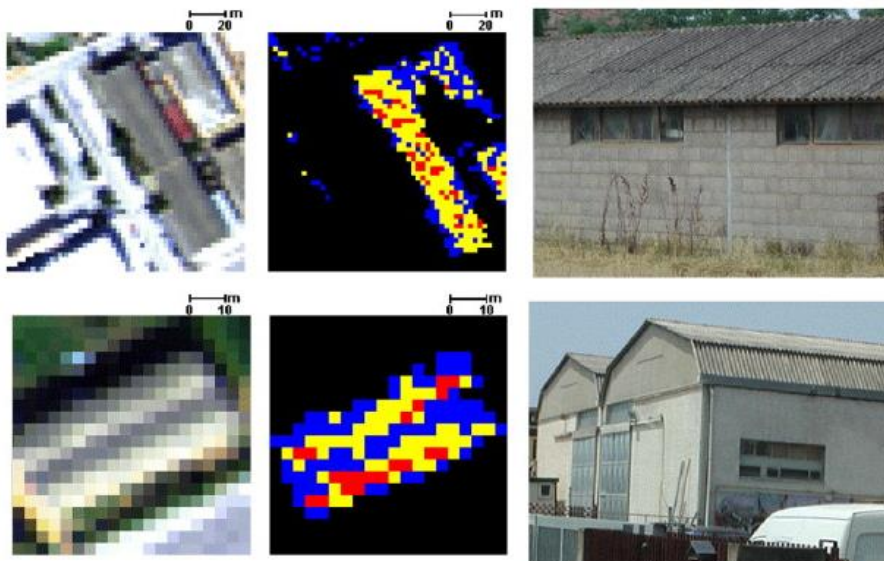
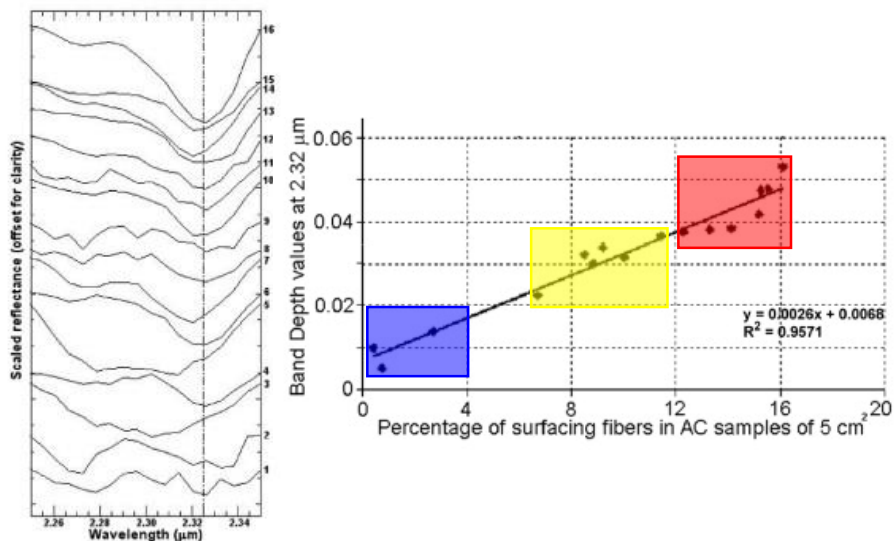


Geological map (overlaid on a C.T.R. 1:10000 map) with depicted in green colour the serpentinites deposits (not only the outcrops) mapped by CNR geologists in 2010-2011 in the Pollino National Park and used in the validation phase of the SAP4PRISMA project products

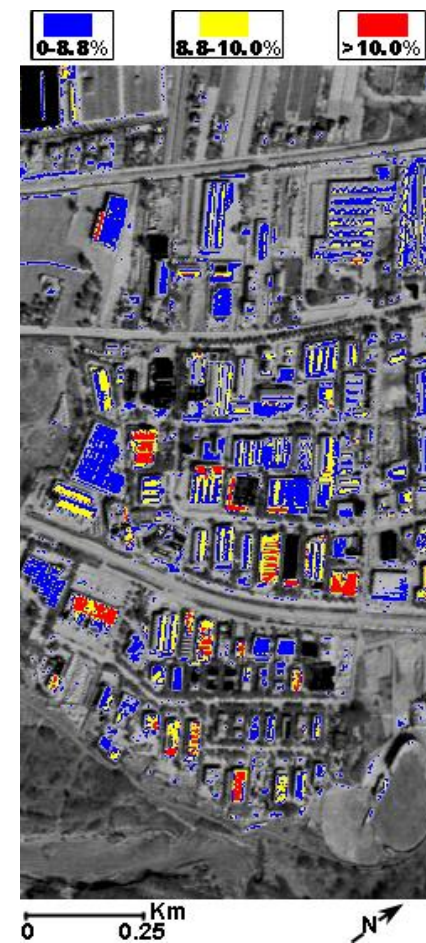
SFF algorithm requires in input a reference spectrum/ROI → not automatic and not quantitative!

Mapping asbestos-cement (AC) roofing sheets using airborne data (1.5 m of GSD)

Samples (#)	2.32 μ m Band Depth (%)	Surfacing fibres (%)
1	0.98	0.4
2	0.50	0.7
3	1.59	2.7
4	2.23	6.7
5	3.22	8.5
6	3.01	8.8
7	3.38	9.2
8	3.14	10.0
9	3.66	11.4
10	3.76	12.3
11	3.81	13.2
12	3.83	14.1
13	4.16	15.2
14	4.72	15.3
15	4.76	15.5
16	5.39	16.1



AC deterioration status map in the Follonica industrial area using MIVIS airborne data

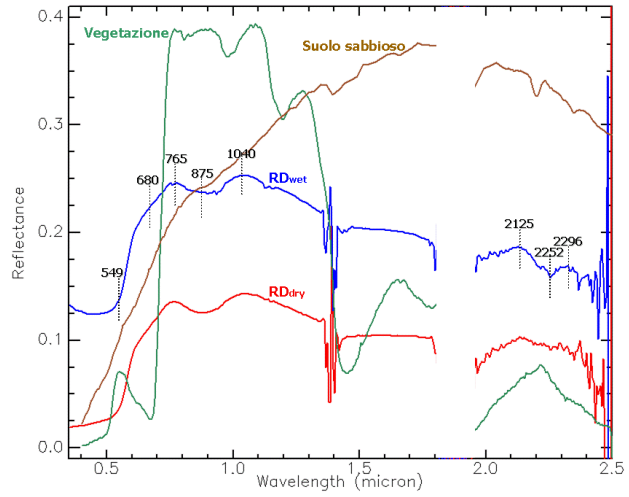


AC deterioration status map in the Rimini industrial area using MIVIS airborne data

Bassani, C., Cavalli, R.M., Cavalcante, F., Cuomo, V., Palombo, A., Pascucci, S., Pignatti, S. *Deterioration status of asbestos-cement roofing sheets assessed by analyzing hyperspectral data* (2007) *Remote Sensing of Environment*, 109 (3), pp. 361-378.

Mapping industrial pollutant: results for red dust using Hyperion dataset

Selection of the RD characteristic bands using ASD *in situ* collected data (Podgorica Aluminum Plant, 2008) and lab spectra (2012) and analysis (XRD+XRF)



RM composition

Fe ₂ O ₃	30–60 wt%
Al ₂ O ₃	10–20 wt%
SiO ₂	3–50 wt%
Na ₂ O	2–10 wt%
CaO	2–8 wt%
TiO ₂	Trace-25 wt%



Pascucci et al., 2012. *Using imaging spectroscopy to map red mud dust waste: The Podgorica Aluminum Complex case study. Remote Sens. of Environm., 2012*, 123, pp. 139-154

→ Tuning of the **RDI_{PRISMA}** index

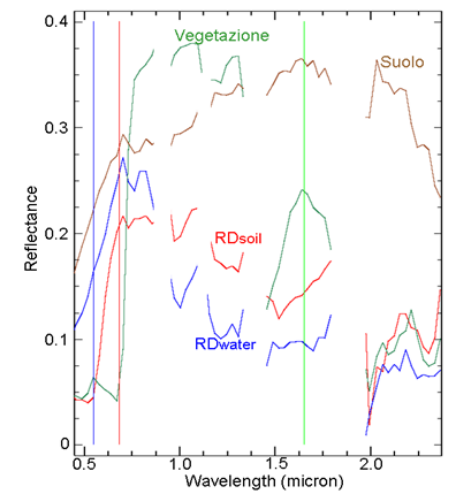
$$RDI_{PRISMA} = \frac{\lambda_{679} - \lambda_{554}}{\lambda_{2251} + \lambda_{679} + \lambda_{554}}$$

Calculation of the optimal threshold value for the **RDI_{PRISMA}** index for the real case of a PRISMA-like imagery that allows to obtain a correct assessment of the distribution of RD

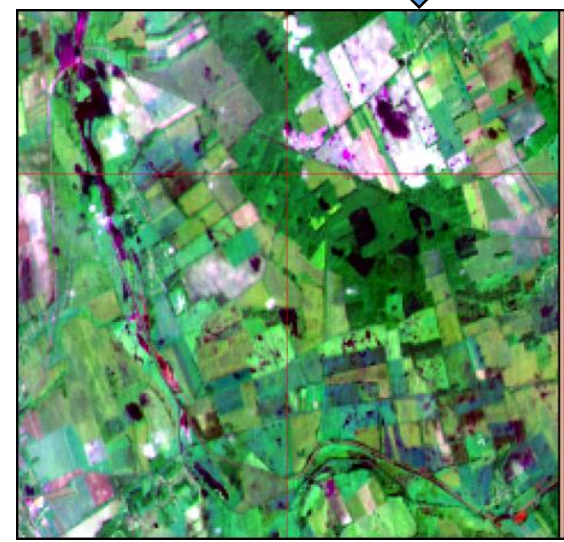
For index values ranging from -1 to 1 → variability range (optimal for the RD detection on soils) from 0.25 to 0.35

Optimal treshold value for the 2010 Hyperion imagery is 0.28

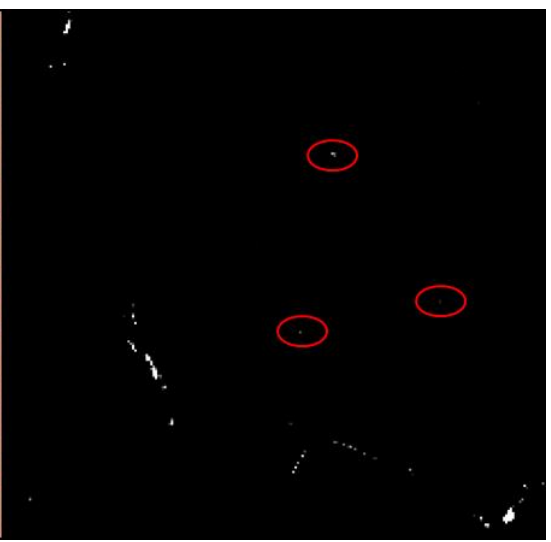
Classification: Overall Accuracy > 0.88 and K > 0.8



Reflectance spectra extracted from Hyperion imagery (2010)



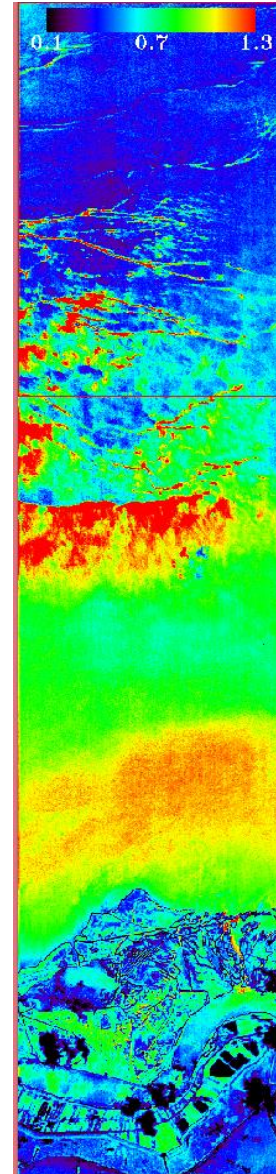
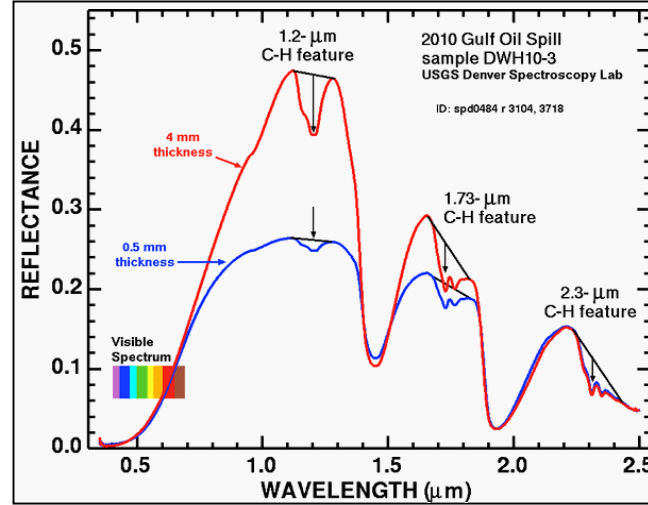
Hyperion reflectance imagery resize (9/10/2010) R:681;G:1649;B:559nm



RD map obtained by applying the **RDI index** and a treshold of 0.28

Mapping oil spill on sea waters: example results on Hyperion dataset

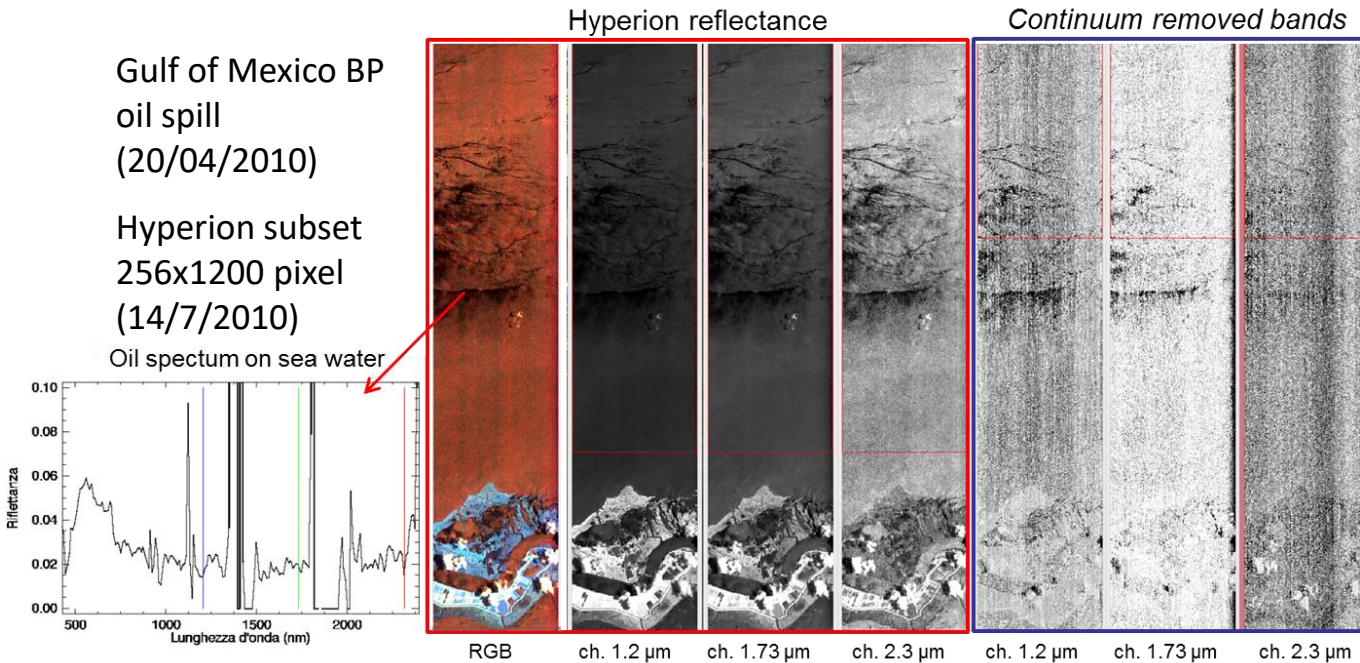
The analysis of oil field spectra (USGS) on sea waters show that the best spectral information of the spilled oil on water is in the 300-600nm (UV-VIS) spectral range and between 1100 and 1300nm (NIR) and some minor features occur between 1600 and 1750nm (NIR) and 2200-2400 (SWIR) related to the oil C-H combinations, but it strongly depends on the oil film thickness and API



Oil spill map obtained applying the Spectral Feature Fitting (SFF) algorithm on Hyperion reflectance imagery (0.48-2.3 µm), which allows a qualitative mapping of the emulsion of spilled oil

In red the areas affected by the floating oil pollution on the sea surface of the Gulf of Mexico

Leifer et al., 2012. *State of the art satellite and airborne marine oil spill remote sensing: Application to the BP Deepwater Horizon oil spill. Remote Sens. of Environm., 2012, 124, pp. 185-209*



Conclusions and future work

- ✓ The advent of HYS will allow the mapping of the physical and chemical characteristics of agricultural soils (in the first 30 cm of soil) like:
 - Texture (% of clay, silt and sand)
 - % of soil organic carbon - SOC
- ✓ The availability of new HYS imagery will
 - impact on the retrieval of parameters pertaining to agronomical management ;
 - improve surface pollutants assessment, according to the sensor performances especially in the **SWIR range**
- ✓ From 2018 PRISMA & ENMAP hyperspectral 30m/pixel images will be available to the community (**data policy and user-friendly interface for images downloading?**)
- ✓ In the near future the higher spatial resolution (**GSD \leq 10 m**) and the **wider swath** of the next HYS missions will **improve** soil mapping within precision agriculture and surface pollutants mapping;
- ✓ Forthcoming missions, like HypsIRI and SHALOM will fill these gaps both in terms of spatial resolution and full spectral coverage from VSWIR to **LWIR** (e.g., useful for SOC or discharges estimation)