Assessment of Approaches for the Mitigation of Confounding Effects in PRISMA and EnMAP Retrieval of Topsoil Properties

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ESA Symposium on Earth Observation for Soil Protection and Restoration

Limitation of hyperspectral data for soil properties retrieval

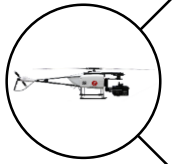
Hyperspectral data for soil properties retrieval

Laboratory spectroscopy

- No spectral mixing
- Discrete measurement
- Costly to repeat

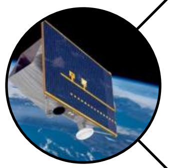
Field spectroscopy

- Low spectral mixing
- Point measurements and costly
- Costly to repeat



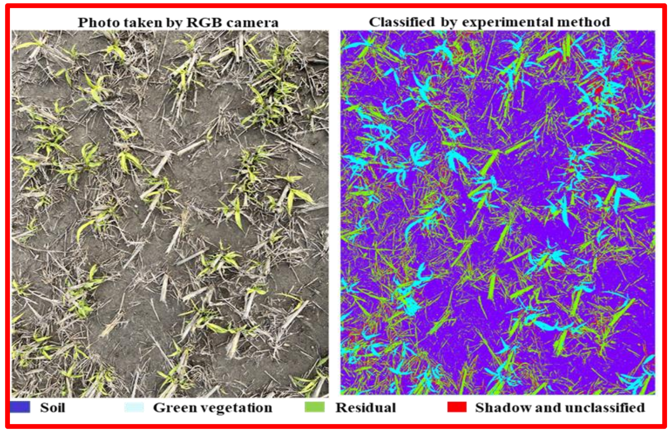
Airborne image spectroscopy

- Medium spectral mixing
- Spatially continuous measurement (local)
- Costly to repeat



Spaceborne image spectroscopy

- High spectral mixing
- Spatially continuous measurement (local to regional)
- Medium revisit time



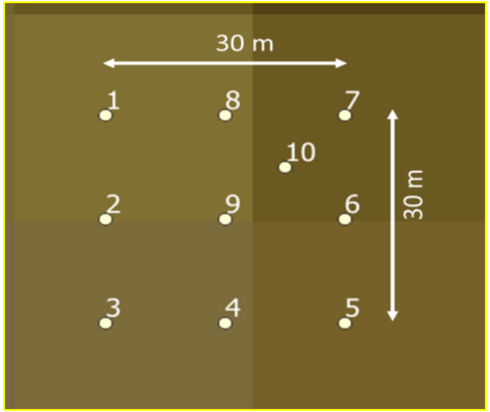
External parameters effect minimizing

External (non-wanted) parameters effect minimizing

- **Known external parameter quantity**
  - A Priori correction
  - Post correction
- **Unknown External parameter quantity (Remote sensing)**
  - Optimization of the train sample basis
  - Preprocessing methods — **Smoothing, SNV, Derivative, Absorbance, Detrending baseline**
  - Chemometric methods — **EPO, DS, PDS, OSG, GLSW**
  - Radiative transfer model — **MARMIT (soil moisture)**

In-situ data gathering and image acquisition (Italy)

Elementary Sampling Unit



Installation of Soil Moisture Sensors

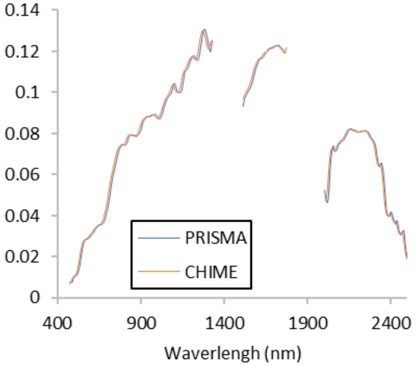
PRISMA Dataset (3 test sites: Jolanda, Maccarese, Pignola)

Totally 20 PRISMA images (2019-2023), n = 635

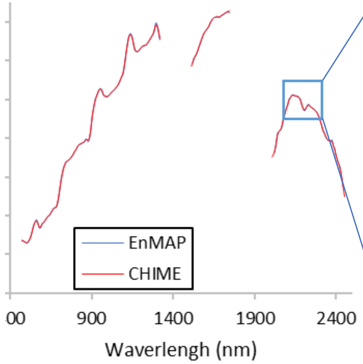
Variable	Min	Max	Mean	Std
Clay (%)	4.4	79.8	42.7	20.5
Silt (%)	1.1	64.7	26.1	15.8
Sand (%)	2.8	93.0	31.2	28.4
SOC (%)	0.2	6.4	1.8	1.6

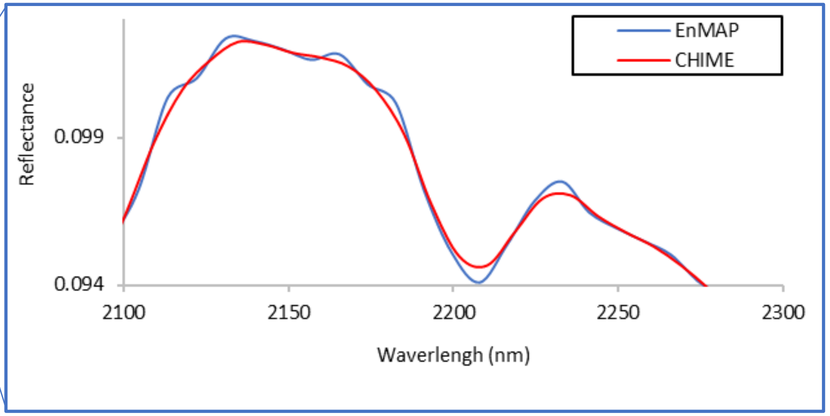
CHIME simulation

PRISMA 2024/01/22



EnMAP 2024/01/22





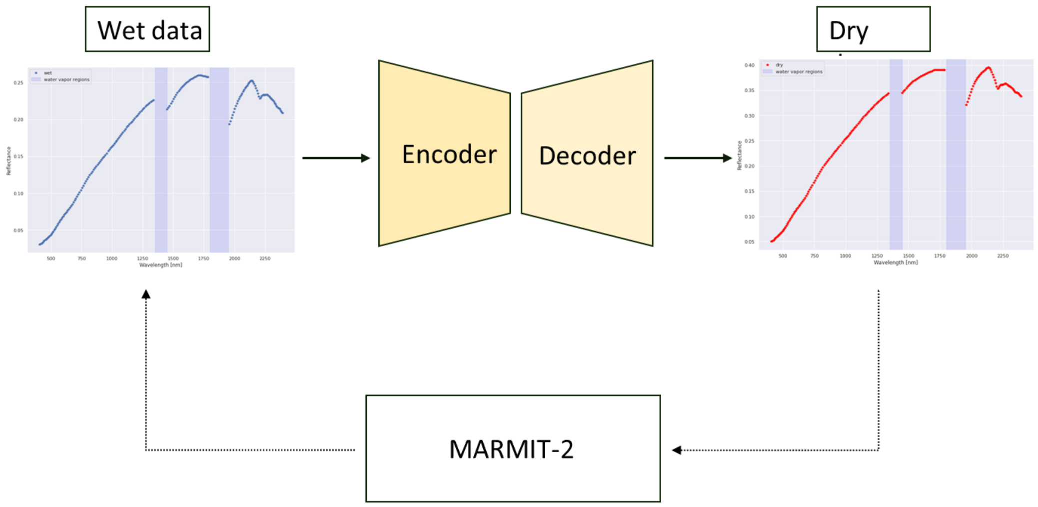
EnMAP Dataset (1 test site: Jolanda)

Totally 5 EnMAP images (2022-2023), n = 103

Variable	Min	Max	Mean	Std
Clay (%)	23.2	73.8	54.2	15.3
Silt (%)	21.0	64.7	36.8	12.6
Sand (%)	2.8	22.0	9.0	5.3
SOC (%)	0.6	8.9	3.6	2.3

Minimizing the external parameters effect of reflectance

Multilayer rAdiative tRansfer Model of soIl reflecTance (MARMIT)



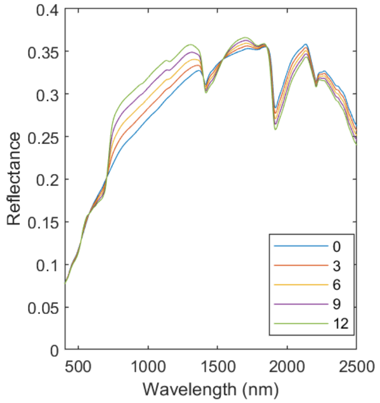
$$X = XP + XQ + R$$

(i) Useful component attributable to selected parameter(s),

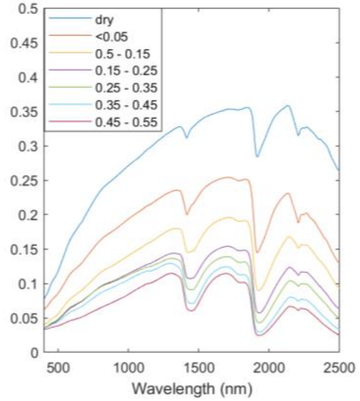
(ii) A parasitic component attributable to non-selected parameter(s),

(iii) Independent residual

Green vegetation

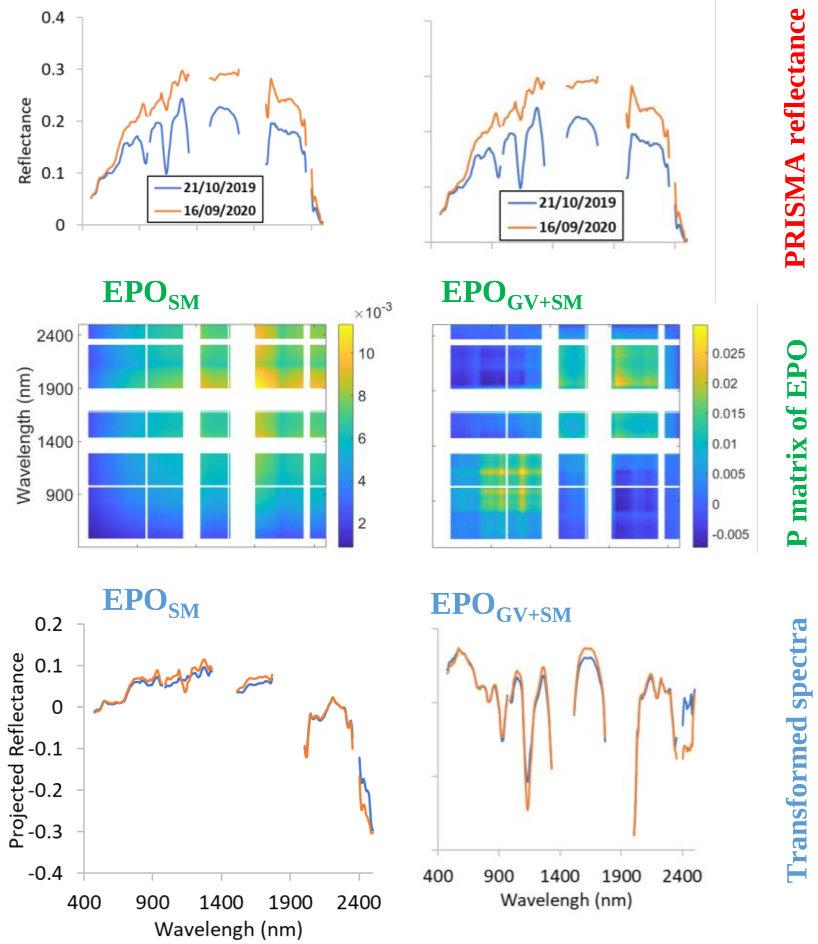


Moisture



External Parameter Orthogonalization (EPO)

A soil sample of Jolanda with clay loam texture



Finding optimum preprocessing method and machine learning algorithms for PRISMA

PRISMA

Without EPO

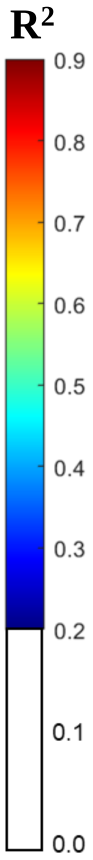
Property	Model	Absorbance	Derivative	Lowess	Median filter	Reflectance	Savitzky–Golay	SG0_det_bas	*SG1abso	SG2abso	SNV_SG1_abs	SNV_SG2_abs	SNVabsor	SNVrefl	zangf_br
Clay	Cubist														
Clay	*GPR	0.59	0.73	0.69	0.65	0.65	0.65	0.63	0.72	0.7	0.69	0.63	0.63	0.64	0.63
Clay	PLSR														
Clay	RF		0.39						0.44	0.34	0.21	0.23			
Clay	SVR														
Silt	Cubist			0.3	0.21	0.25						0.29			
Silt	*GPR	0.61	0.78	0.6	0.6	0.61	0.61	0.61		0.78	0.76	0.74	0.57	0.57	0.61
Silt	PLSR														
Silt	RF									0.37	0.29	0.55			
Silt	SVR														
Sand	Cubist					0.56	0.62			0.32					
Sand	*GPR	0.71	0.81	0.69	0.73	0.72	0.71	0.67	0.81	0.79	0.75	0.76	0.74	0.73	0.67
Sand	PLSR														
Sand	RF		0.27	0.39	0.38	0.39	0.34								
Sand	SVR														
SOC	Cubist								0.21	0.2	0.46				
SOC	*GPR	0.63	0.81	0.5	0.63	0.63	0.63	0.6	0.82	0.69	0.78	0.64	0.67	0.68	0.6
SOC	PLSR														
SOC	RF														
SOC	SVR														

EPO Soil Moisture

Property	Model	Absorbance	Derivative	Lowess	Median filter	Reflectance	Savitzky–Golay	SG0_det_bas	* SG1abso	SG2abso	SNV_SG1_abs	SNV_SG2_abs	SNVabsor	SNVrefl	zangf_br
Clay	Cubist								0.25						
Clay	*GPR	0.68	0.75	0.67	0.68	0.68	0.68	0.64	0.75	0.7	0.69	0.64	0.58	0.59	0.64
Clay	PLSR														
Clay	RF		0.41	0.31	0.29	0.28	0.27		0.37	0.45		0.22			
Clay	SVR														
Silt	Cubist					0.28					0.28				
Silt	*GPR	0.6	0.81	0.59	0.58	0.6	0.59	0.65	0.79	0.77	0.77	0.73	0.64		0.65
Silt	PLSR														
Silt	RF		0.32							0.32	0.45	0.49			
Silt	SVR														
Sand	Cubist		0.46						0.45						
Sand	*GPR	0.66	0.83		0.64	0.66	0.65	0.68	0.82	0.79	0.75	0.77	0.78	0.77	0.68
Sand	PLSR														
Sand	RF		0.26	0.27	0.38	0.25	0.33								
Sand	SVR														
SOC	Cubist											0.25	0.35	0.42	
SOC	*GPR	0.7	0.8	0.7	0.68	0.7	0.7	0.66	0.81	0.69	0.77	0.65	0.68	0.67	0.66
SOC	PLSR														
SOC	RF	0.23													
SOC	SVR														

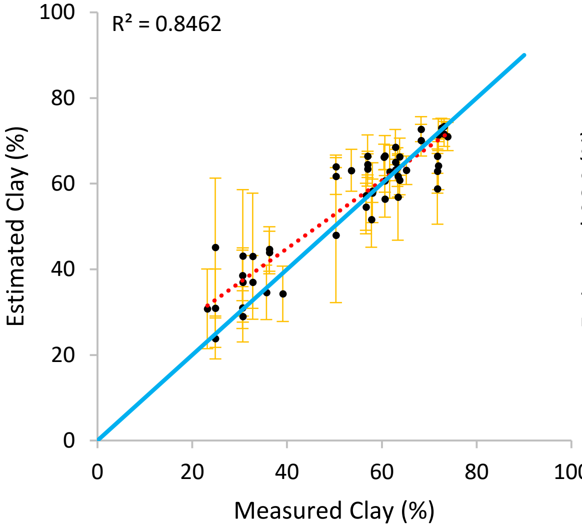
EPO Soil Moisture and Green Vegetation

Property	Model	Absorbance	Derivative	Lowess	Median filter	Reflectance	Savitzky–Golay	SG0_det_bas	*SG1abso	SG2abso	SNV_SG1_abs	SNV_SG2_abs	SNVabsor	SNVrefl	zangf_br
Clay	Cubist														
Clay	*GPR	0.76	0.78	0.76	0.74	0.76	0.76	0.68	0.79	0.72	0.73	0.67	0.71	0.69	0.68
Clay	PLSR														
Clay	RF	0.43	0.45	0.25	0.26	0.21	0.33		0.46	0.47	0.29	0.33	0.21	0.22	
Clay	SVR														
Silt	Cubist					0.35					0.37		0.21	0.22	
Silt	*GPR	0.72	0.79	0.7	0.7	0.72	0.71	0.69	0.8	0.76	0.79	0.75	0.72	0.73	0.69
Silt	PLSR														
Silt	RF	0.39	0.35					0.33	0.4	0.33	0.44		0.47	0.48	0.32
Silt	SVR														
Sand	Cubist		0.42		0.34					0.25	0.47		0.31	0.48	
Sand	*GPR	0.78	0.83	0.81	0.81	0.79	0.78	0.79	0.84	0.8	0.81	0.78	0.74	0.74	0.79
Sand	PLSR														
Sand	RF	0.26	0.27						0.3	0.23	0.36				
Sand	SVR														
SOC	Cubist	0.28	0.28							0.37		0.22		0.48	
SOC	*GPR	0.79	0.8	0.79	0.79	0.79	0.78	0.74	0.81	0.67	0.78	0.67	0.74	0.73	0.74
SOC	PLSR														
SOC	RF	0.39							0.35	0.25					
SOC	SVR														

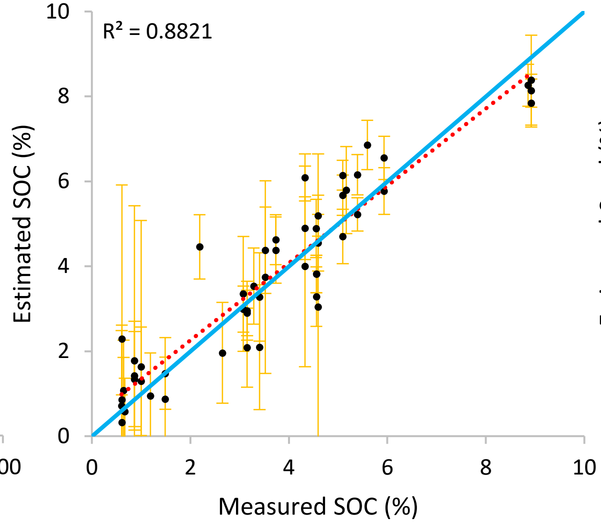


Produce soil properties maps from PRISMA - CHIME image

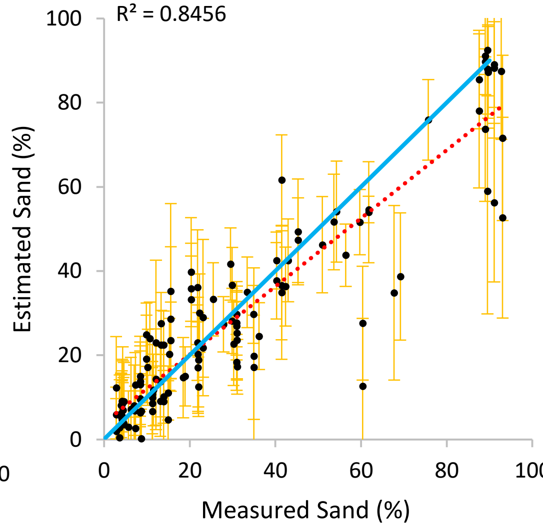
Clay



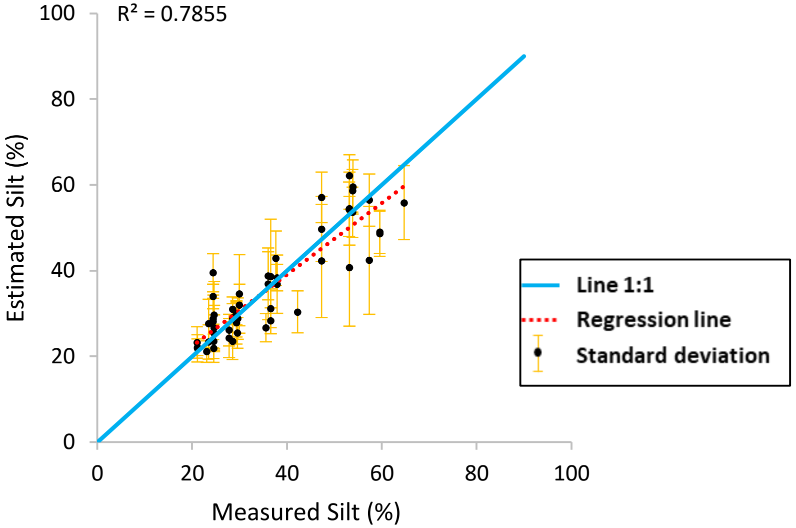
SOC



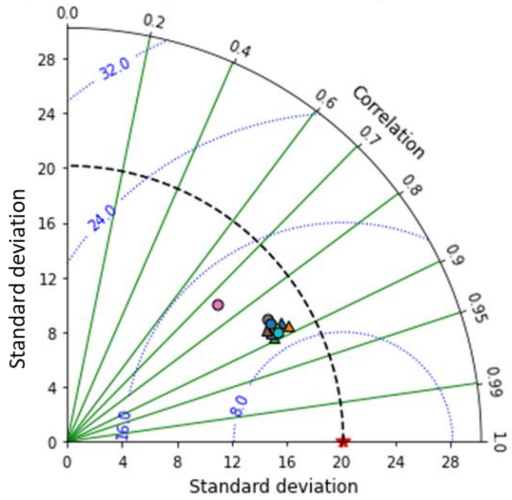
Sand

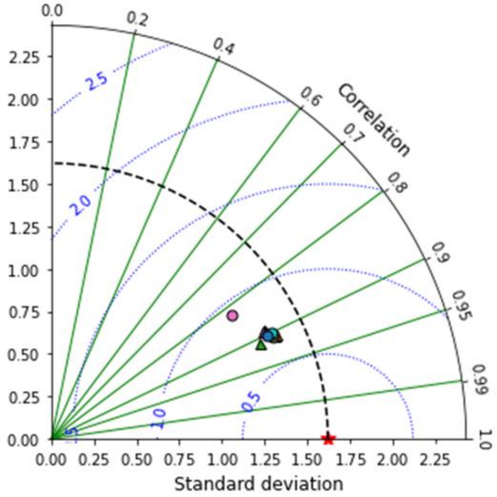


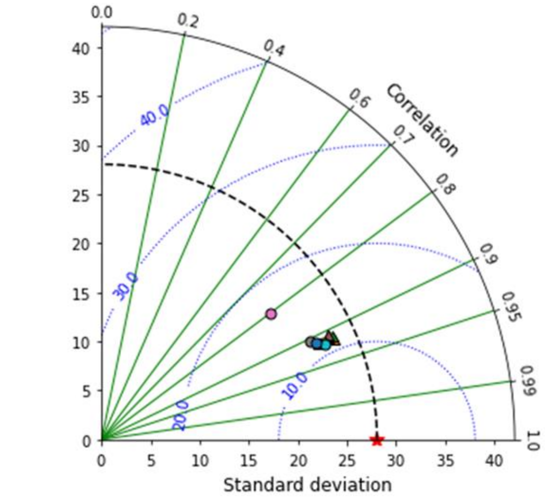
Silt

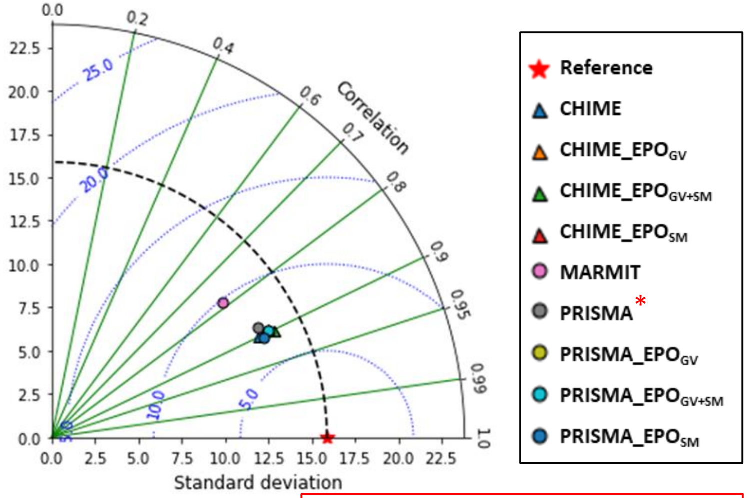


PRISMA 2023/04/07







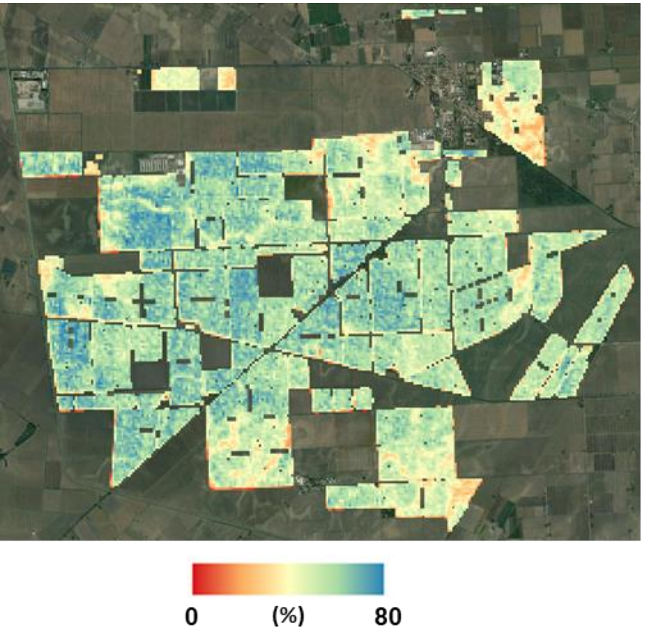


* MARMIT was trained just on laboratory data over the Maccarese site

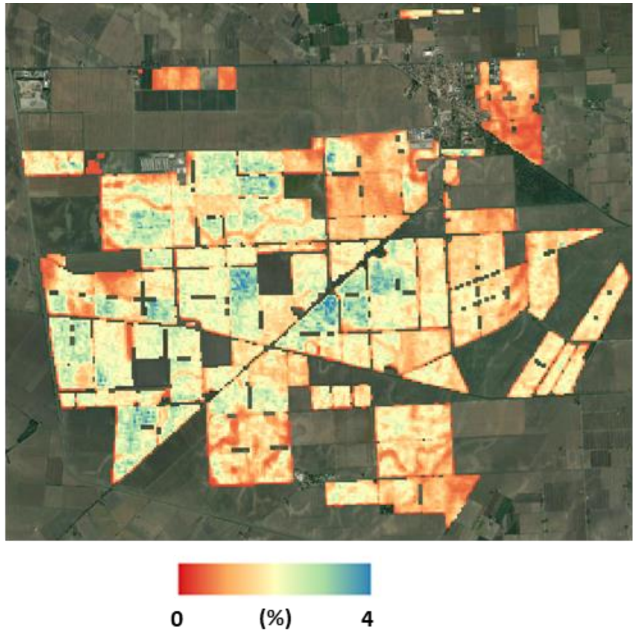
Produce soil properties maps from PRISMA image

1. **Sensor**: PRISMA
2. **Site**: Jolanda farm
3. **Acquisition**: 2023/04/07

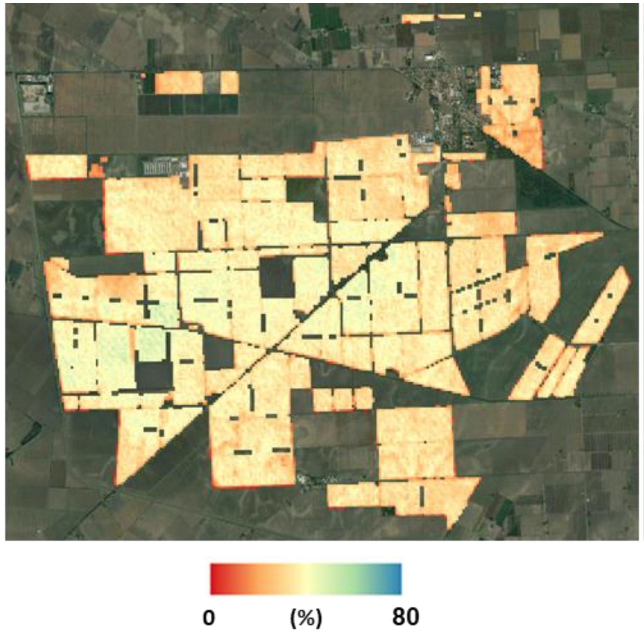
Clay



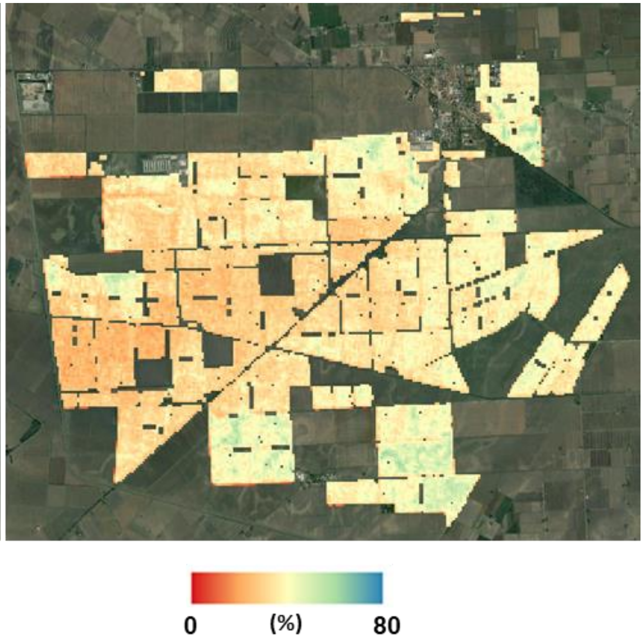
SOC



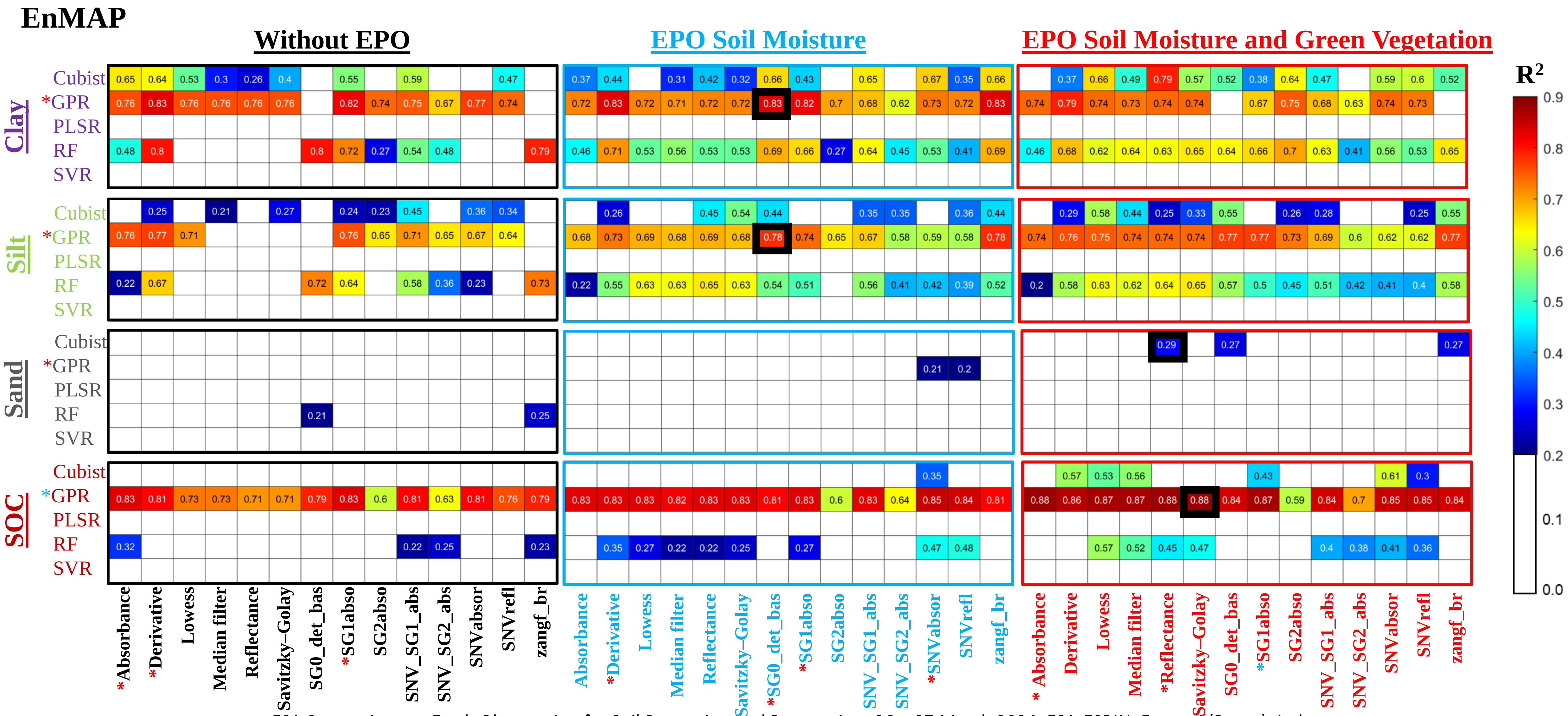
Sand



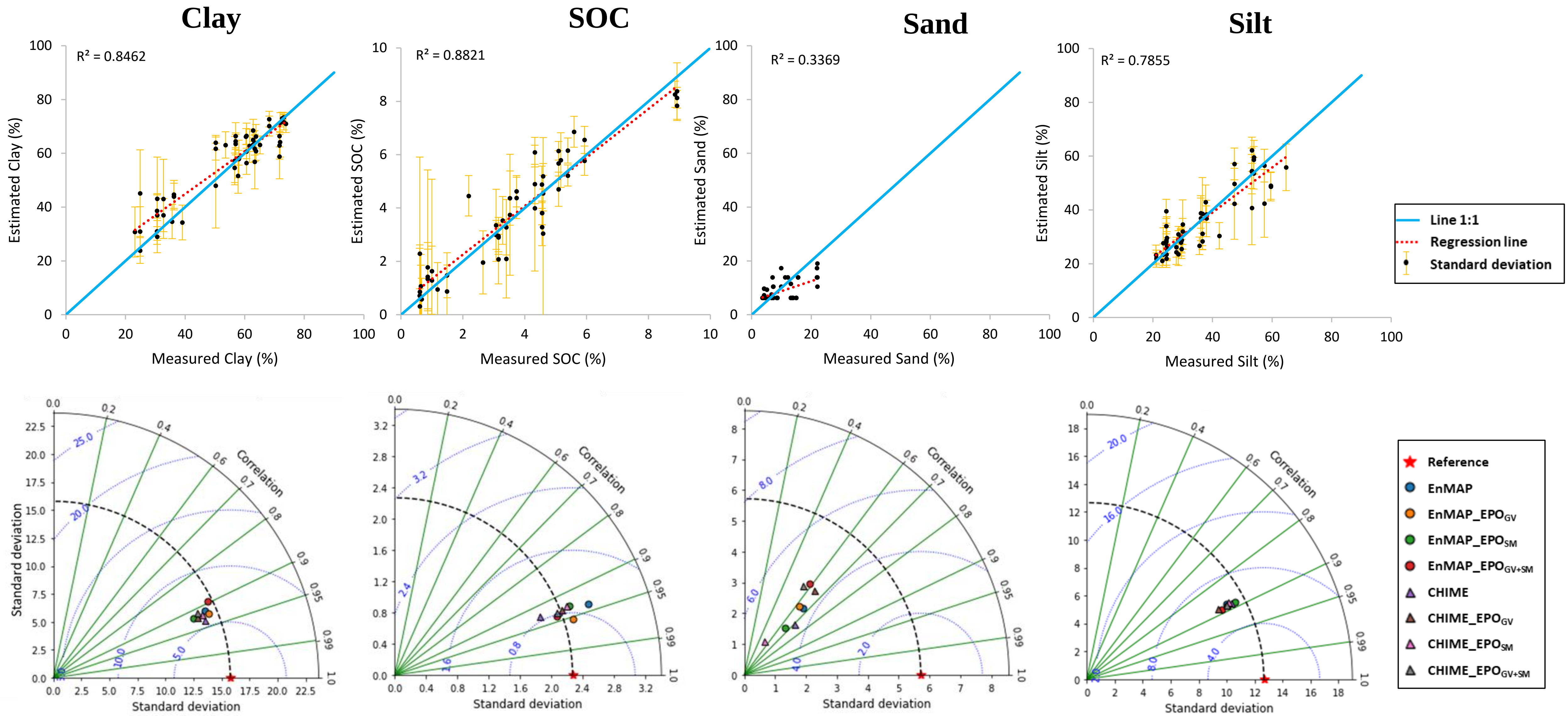
Silt



Finding optimum preprocessing method and machine learning algorithms for EnMAP



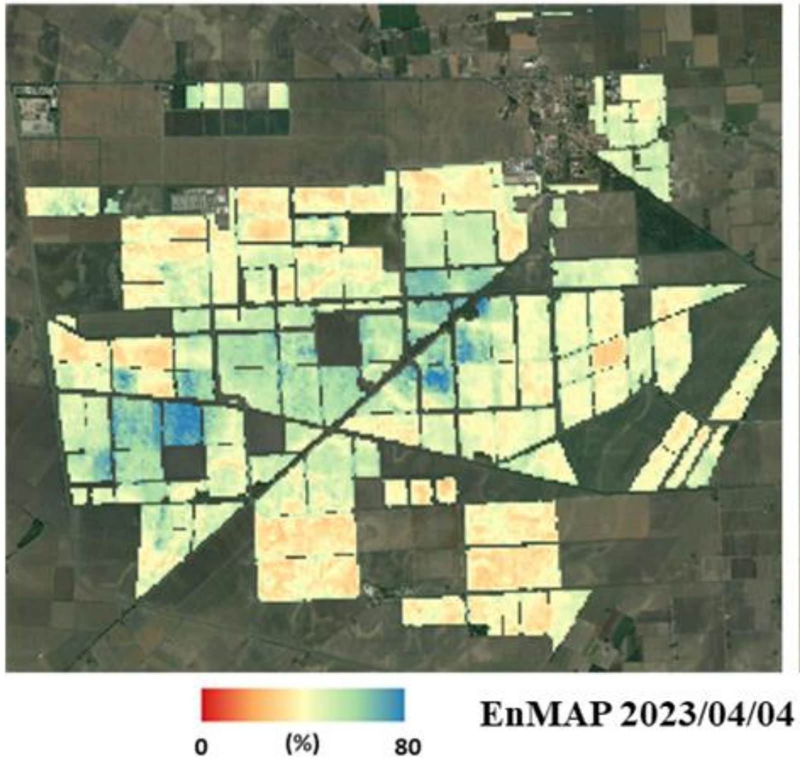
Produce soil properties maps from EnMAP – CHIME image



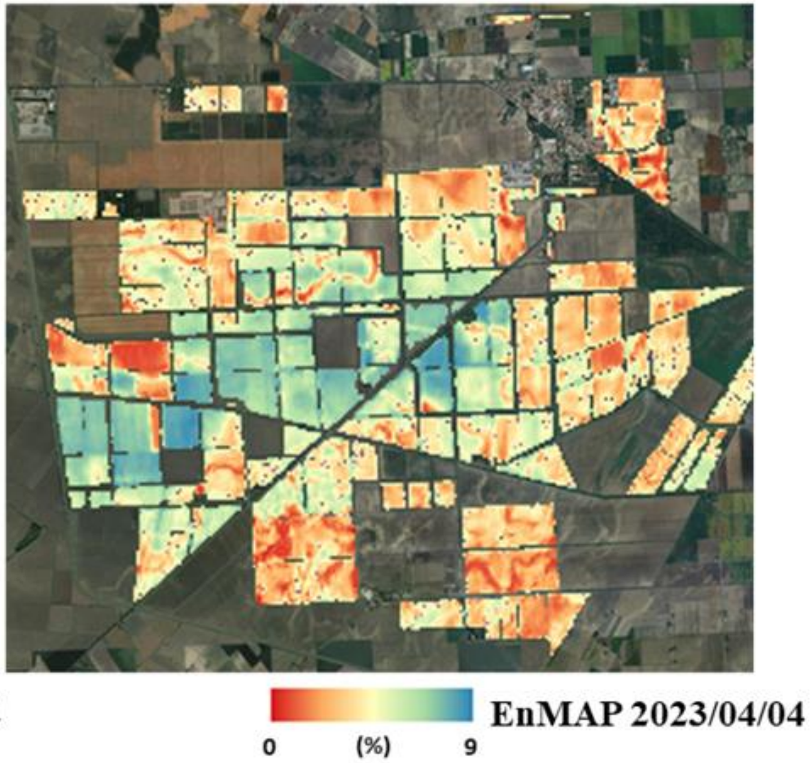
Produce soil properties maps from EnMAP image

1. **Sensor**: EnMAP
2. **Site**: Jolanda farm
3. **Acquisition**: 2023/04/04

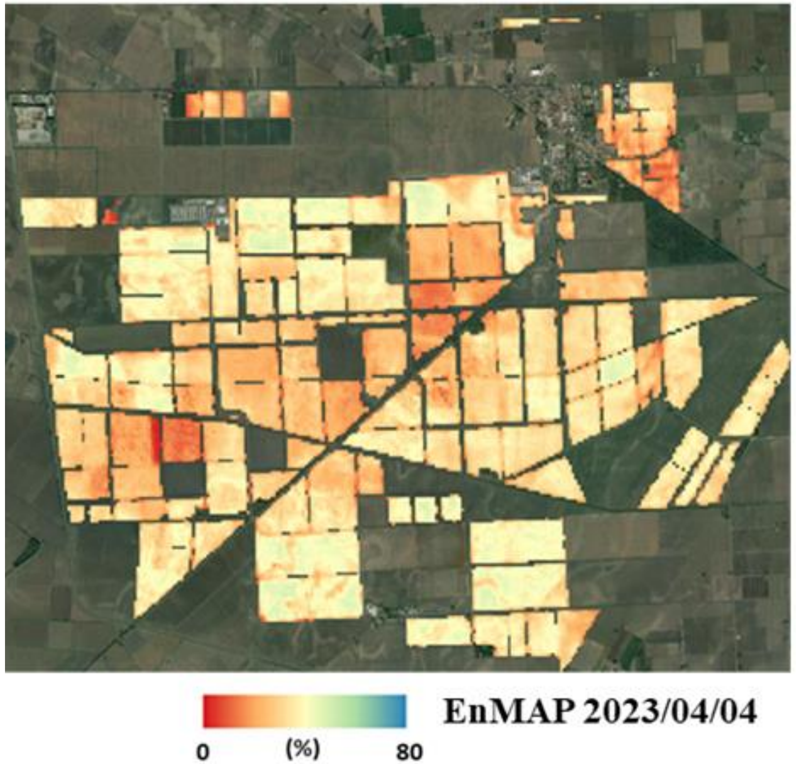
Clay



SOC



Silt



Conclusions

1. The combination of GPR with “MATERN” kernel, with the first order derivative of absorbance spectra smoothed by Savitzky–Golay (frame size = 7, 3th degree polynomial) seems the optimum combination both for PRISMA and EnMAP data.
2. The coupled Green Vegetation to Soil Moisture EPO leads to reduce the variation of estimated value between image acquisitions at different dates and also a slight improving in soil properties estimation.
3. MARMIT is an option to be further investigated to derive dry spectra.
4. CHIME simulated data have suitable capability for soil properties mapping, a simulator is expected. More precise simulation requires spectroscopy or airborne dataset.
5. EnMAP dataset will be completed by including more acquisitions in different sites to fill the gap of the sand data.