Remote sensing of soils : a tool for digital soil mapping.

Challenges and limitations

Gomez C., Vaudour E., Richer-de-Forges A.C.

Webinaire 2024-02-02

- Introduction
- The Center of Scientific Expertise "Digital Soil Mapping"Theia
- Remote sensing to map soils
  - Historical retrospective & general principles
  - Existing programs: Copernicus, Theia
  - Examples of achievements
  - Disturbing factors
- Towards the integration of remote sensing data into digital soil mapping approaches
  - Historical retrospective & general principles
  - Existing programs: *GlobalSoilMap*
  - Examples of achievements
- Conclusion

Introduction

Services provided by soils

Source : FAO, 2015

To protect them and perpetuate the services they provide us

⇒ need to map soils and their properties

Soil data

Soil descriptions:

A soil profile taken from the soil calendar. Source: Gabriela Brändle, Urs Zihlmann, Andreas Chevet.

→ **Soil point data**

National soil mapping programs:

scale 250 000 | scale 50 000 – 100 000 | scale < 50 000

work in progress 1/250 000

sector where soil information exists

https://www.afes.fr/ressources/le-programme-inventaire-gestion-conservation-des-sols-de-france-volet-referentiel-regional-pedologique/

https://www.afes.fr/ressources/la-cartographie-des-sols-a-moyennes-echelles-en-france-metropolitaine/

→ **Static maps without uncertainty quantification**

GisSol
GROUPEMENT D'INTÉRÊT SCIENTIFIQUE SOL

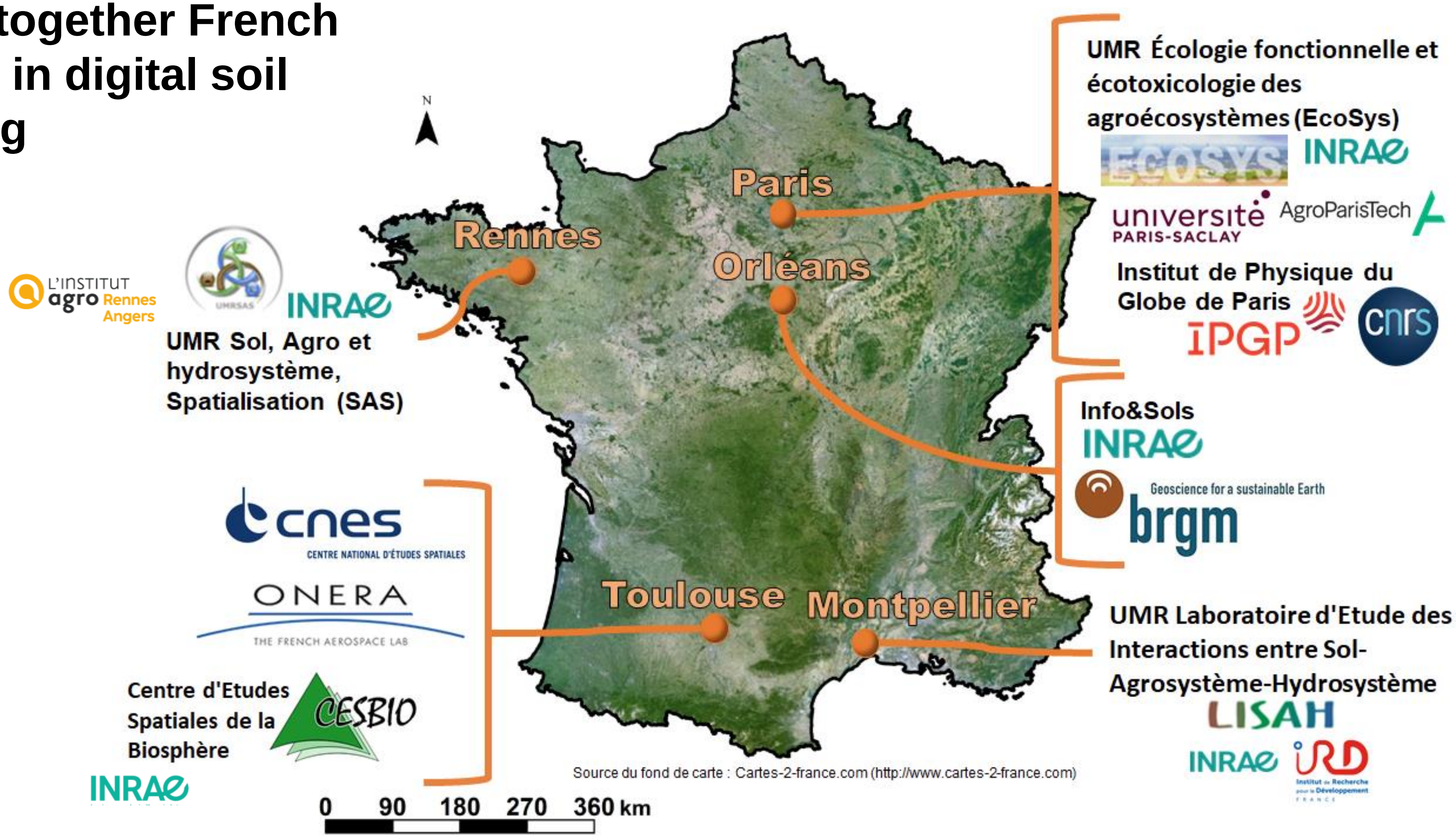
The Center of Scientific Expertise “Digital Soil Mapping” Theia

Digital Soil Mapping
The THEIA network

Theia

The Center of Scientific Expertise "Digital Soil Mapping" Theia

Brings together French experts in digital soil mapping



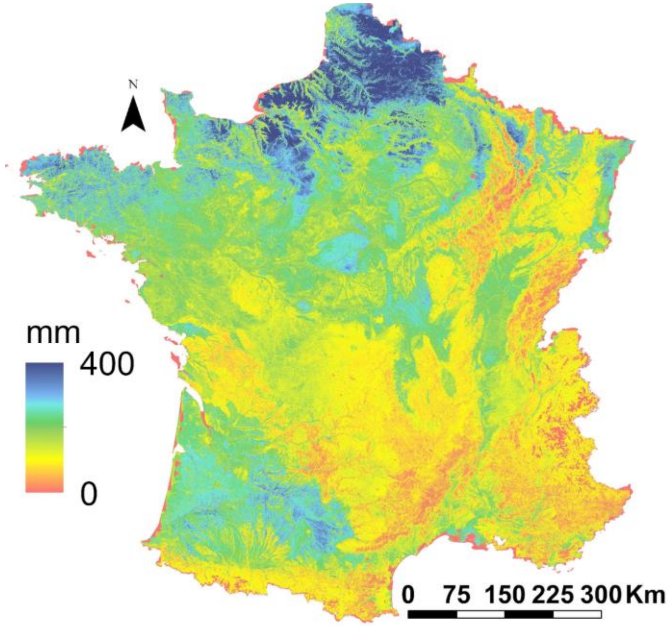
https://www.theia-land.fr/ceslist/ces-cartographie-numerique-des-sols/

Theia Pôle Thématique Surfaces Continentales

The Center of Scientific Expertise “Digital Soil Mapping” Theia

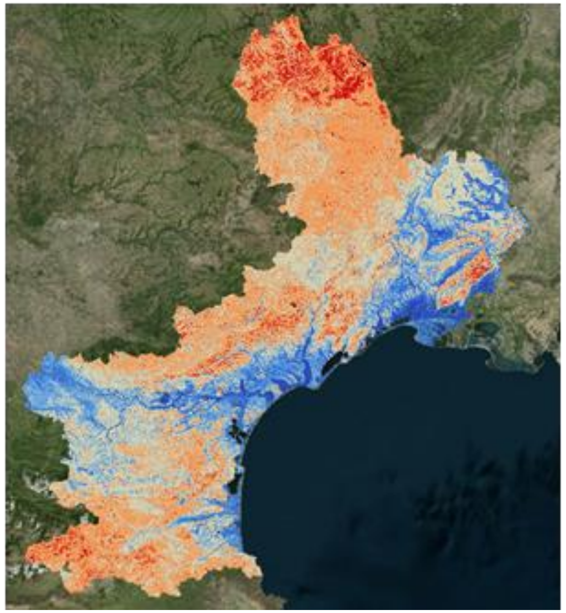
Objective 1 : Produce spatial estimates of soil properties

Available water capacity (AWC) of soils in mainland France (in mm of water)



after Roman Dobarco et al., 2021
https://doi.org/10.15454/9IRARJ

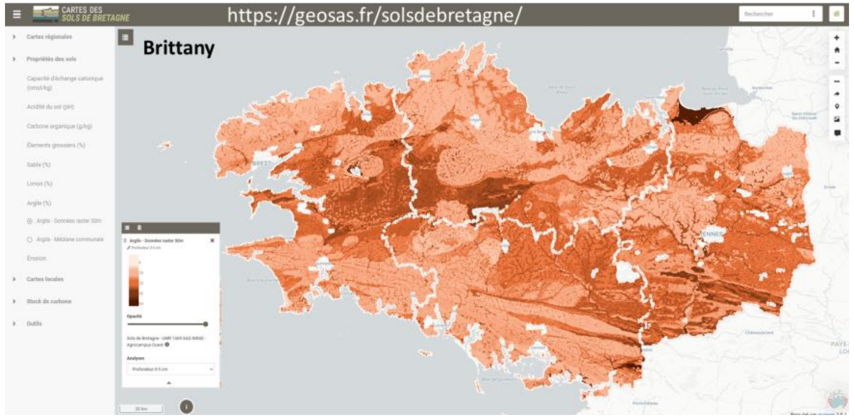
Available water capacity (AWC) of soils in Languedoc-Roussillon



https://ckan.openig.org/dataset/cartes-numeriques-de-proprietes-des-sols-en-languedoc-roussillon

Interactive mapping of soil properties in Brittany

https://geosas.fr/solsdebretagne/



The Center of Scientific Expertise “Digital Soil Mapping” Theia

Objective 2 : Federate and capitalize on efforts in methodologies and algorithms

→ advance digital mapping methods, from sampling, choice of covariates (including those from remote sensing), modeling, and up to validation methods.

Objective 3 : Transfer know-how to operations

Popularization site:

https://cartograph-e.hub.inrae.fr/

French-speaking training planned for 2025

Remote sensing to map soils

Historical retrospective & general principles

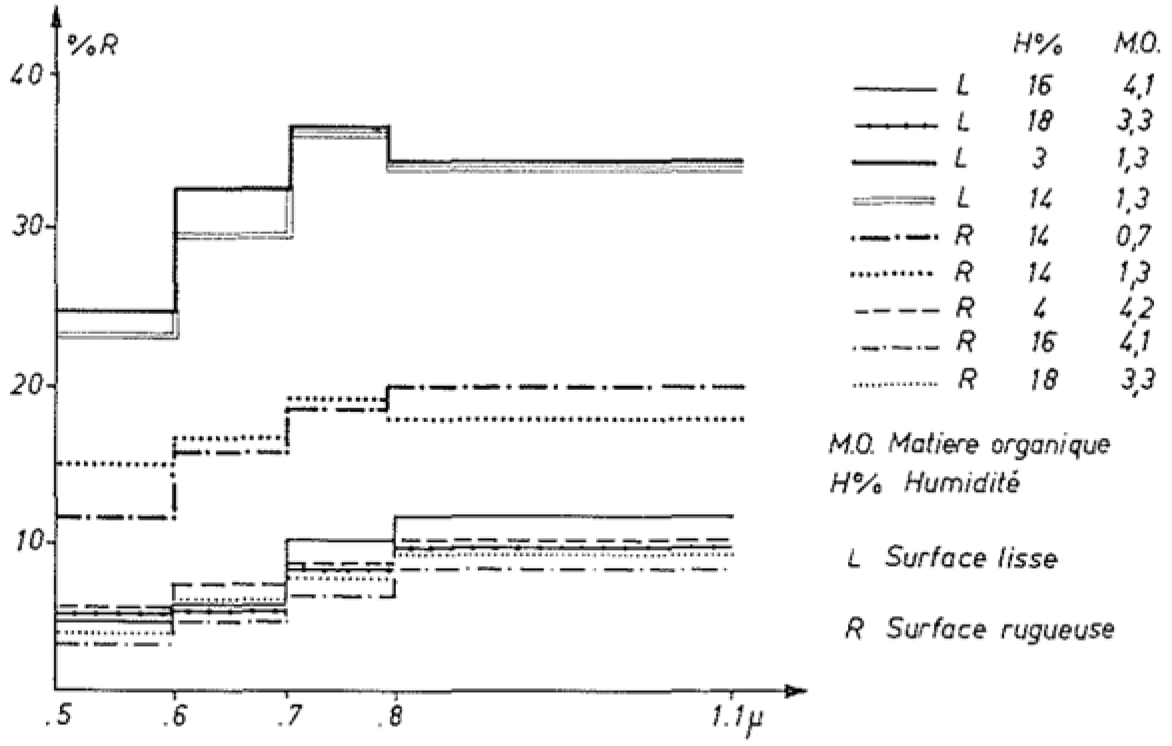


Figure 1 – Courbes de réflectance de sols peu ou pas organiques

Girard, 1978. Emploi de la télédétection pour l'étude de l'humidité des Sols. *Houille Blanche*, *64*, 533–539, doi:10.1051/lhb/1978044

Notion of soil surface condition

“composition and organization of soil surface at a given time”

R. ESCADAFAL, 1989

©UMR EGC-Equipe Sol, March 2012

VAUDOUR E., GIRARD MC., 2010, *Pédologie*, chapitre 23. In Girard MC et Girard CM, Traitement des images de télédétection, Dunod, Paris.

Spectral behaviour and indices of soils

noir : végétation - blanc : eau

Figure IX - Index de brillance sur sols nus

SAINT et al., symp int Avignon 1981

Spectral behaviour and indices of soils

noir : végétation - blanc : eau

Figure IX - Index de brillance sur sols nus

SAINT et al., symp int Avignon 1981

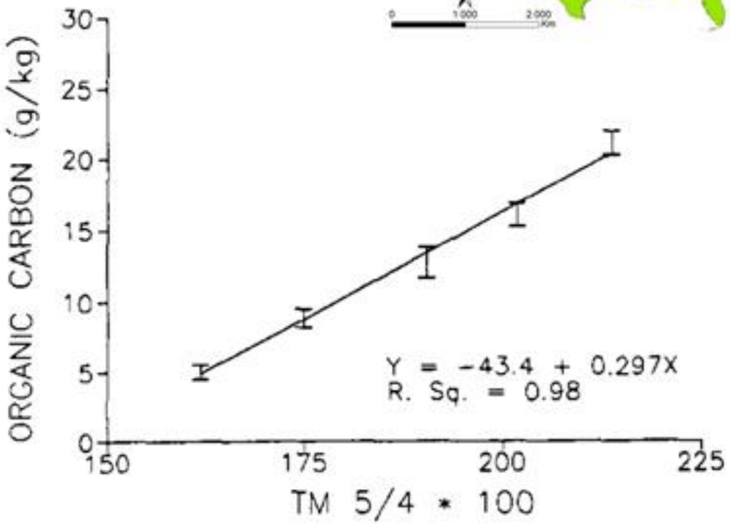


Figure 3. Regression line for organic carbon with TM 5/4. Error bars are standard error of the mean of soil samples.

Frazier and Cheng, 1989 Remote Sensing of Environment
https://doi.org/10.1016/0034-4257(89)90123-5

Spectral behaviour and indices of soils

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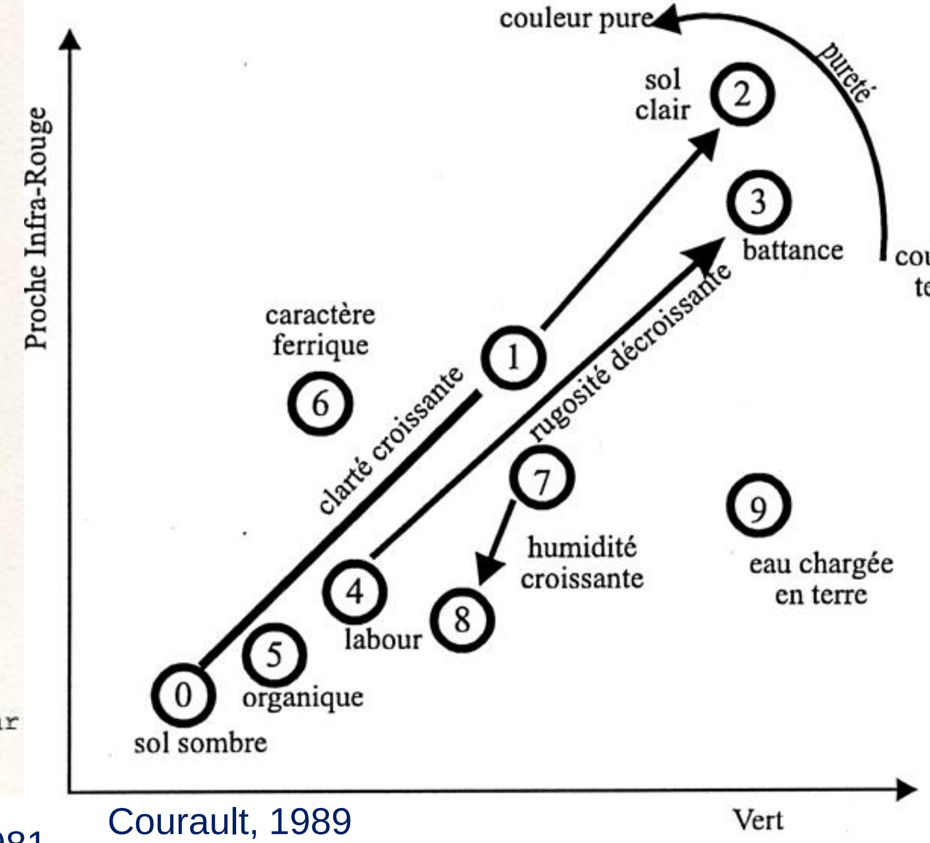
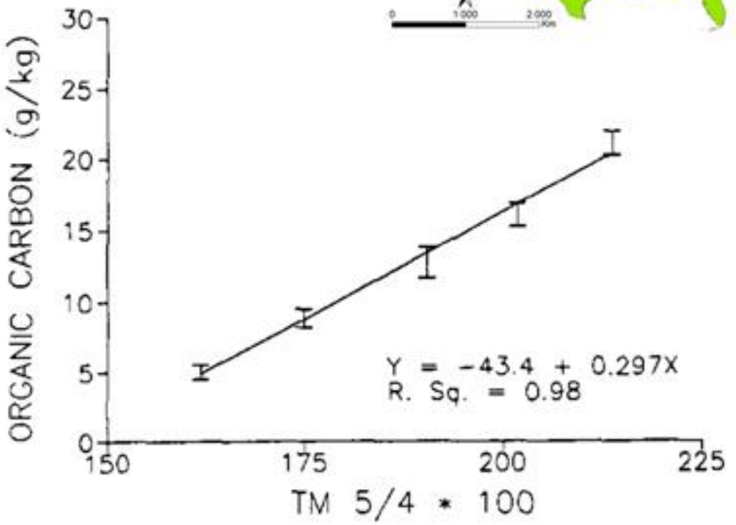
Figure IX - Index de brillance sur sols nus

SAINT et al., symp int Avignon 1981



Courault, 1989



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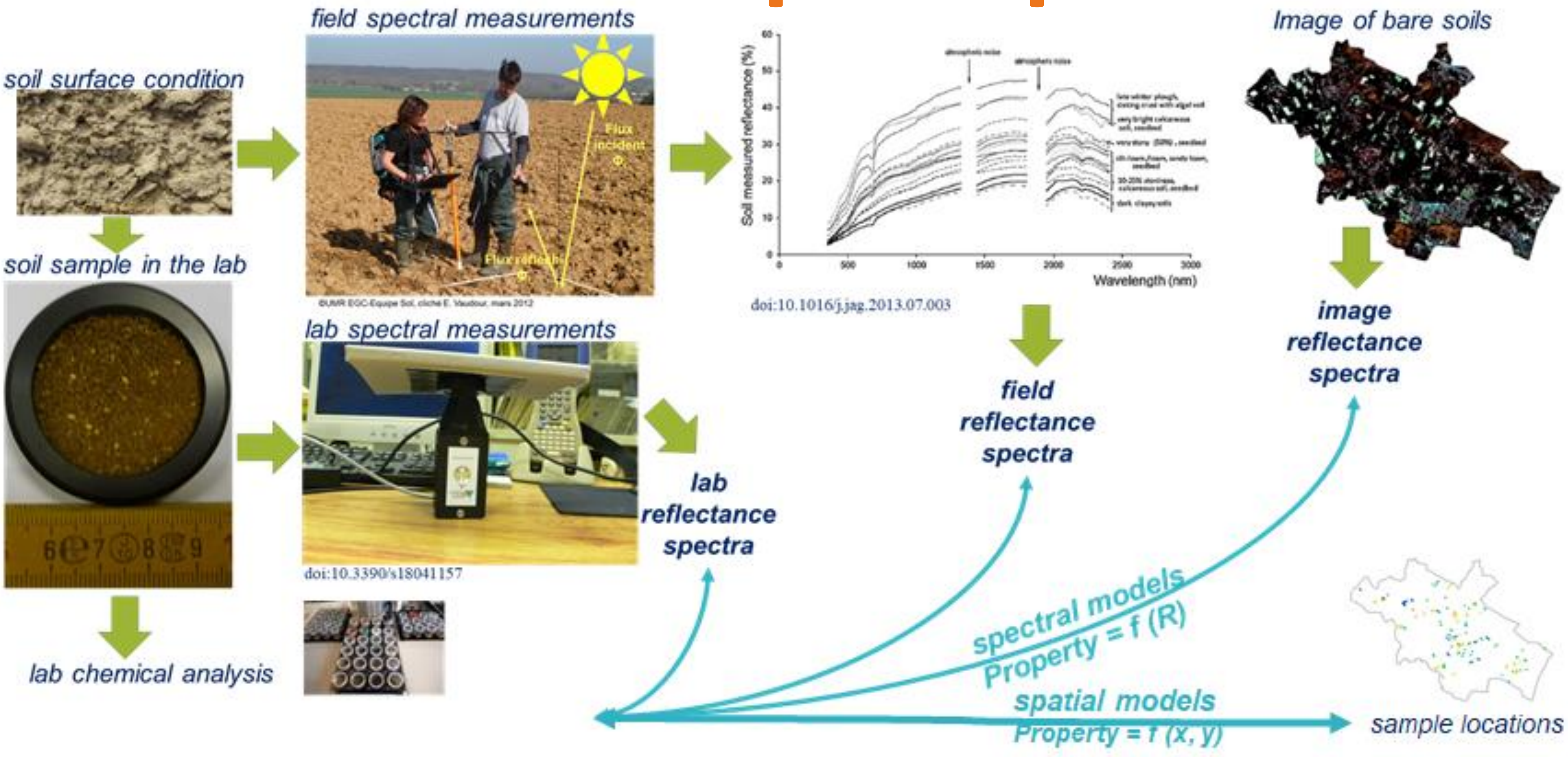
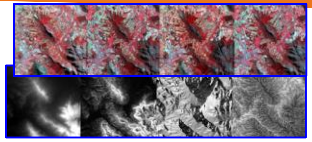
General principles



Vaudour and Wetterlind, 2021. *EJPSOIL Newsletter*

Remote sensing approaches



photogrammetry

DIMITRI

OASIS

CLAPAS

SOILSPECT

Hyperstat

indices

PLSR

image classifications

satellite series

1935 De Martonne

1965 Dupuis & Callot

1980 Girard & Rogala

1988 Girard & King

1989 Escadafal

1990 Girard et al.

1992 Jacquemoud et al.

1994 Robbez-Masson

2008 Gomez et al

2008 Vaudour.

2010 Vaudour et al.

2019 Loiseau et al.

2023 Urbina-Salazar et al.

1941 Jenny

1965 Matheron

1977 Giltrap

1983 Girard

1986 Burrough

2003 Mc Bratney et al.

2009 Sanchez et al.

2014 Arrouays et al.

CLORPT

“soil stats”

“soil geostats”

geomatics

SCORPAN

GlobalSoilMap

Digital Soil Mapping approaches

Remote sensing approaches
photogrammetry
DIMITRI
OASIS
SOILSPECT
CLAPAS
Hyperstat
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1935 De Martonne
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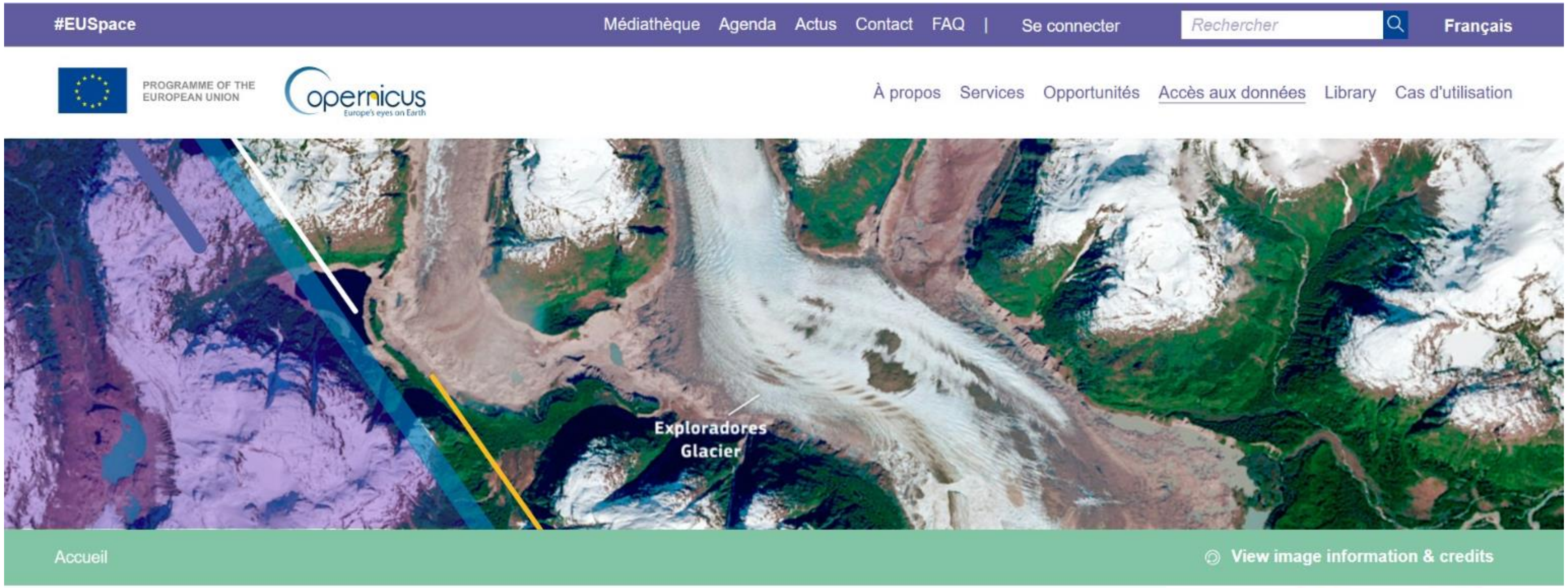
2010 Vaudour et al.
2019 Loiseau et al.
2023 Urbina-Salazar et al.
Digital Soil Mapping approaches

COPERNICUS

Cooperation between:
UE members States
ESA
EUMETSAT
ECMWF
Spatial agencies States



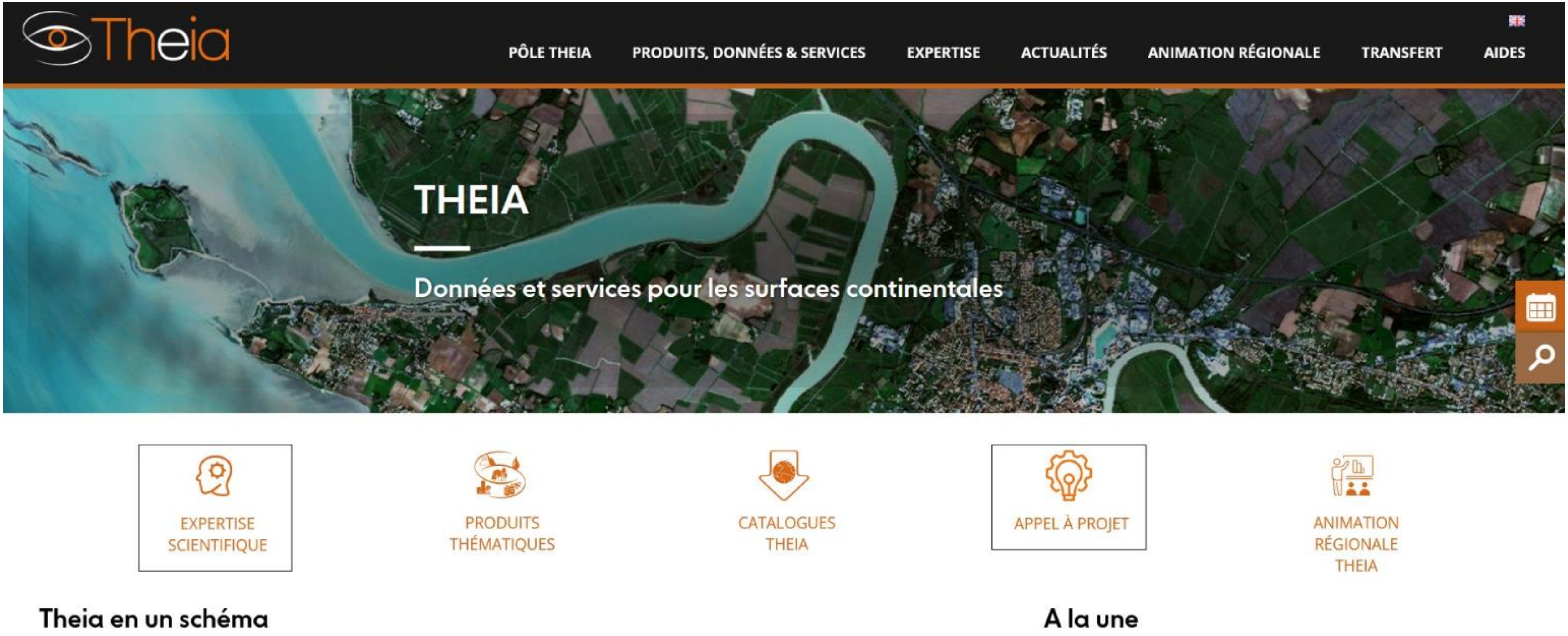
Accès aux données

http://www.copernicus.eu

Families of satellites dedicated to Copernicus *"The Sentinels"*

Contributing missions
from National, European or International organisations

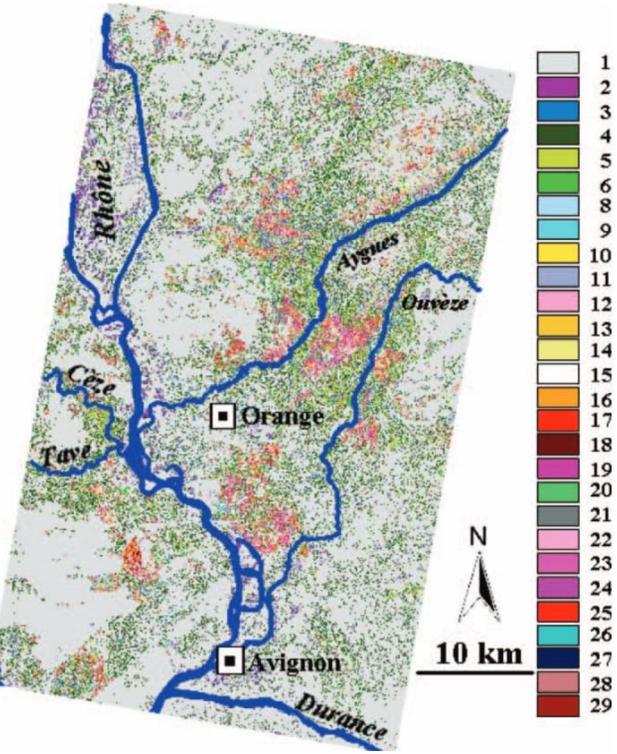
Theia

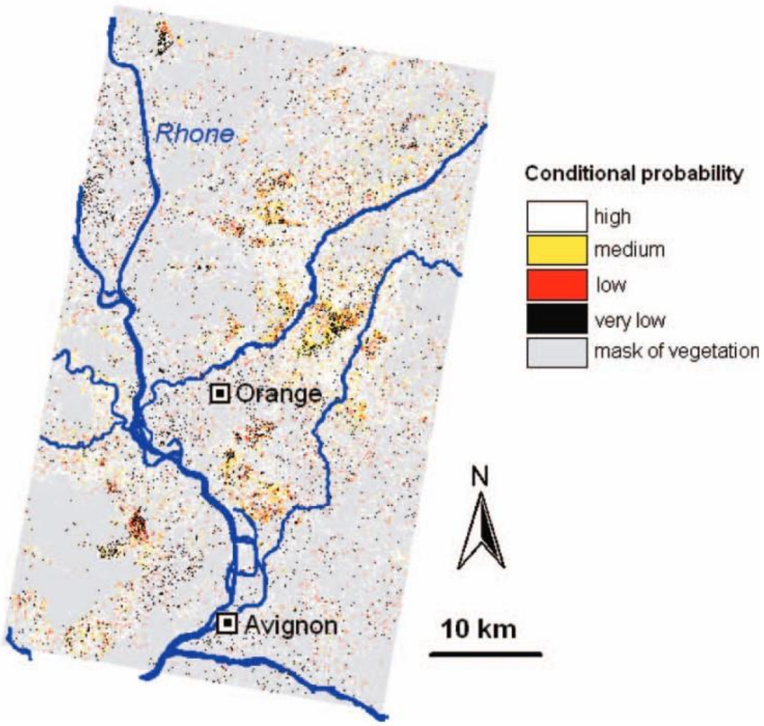


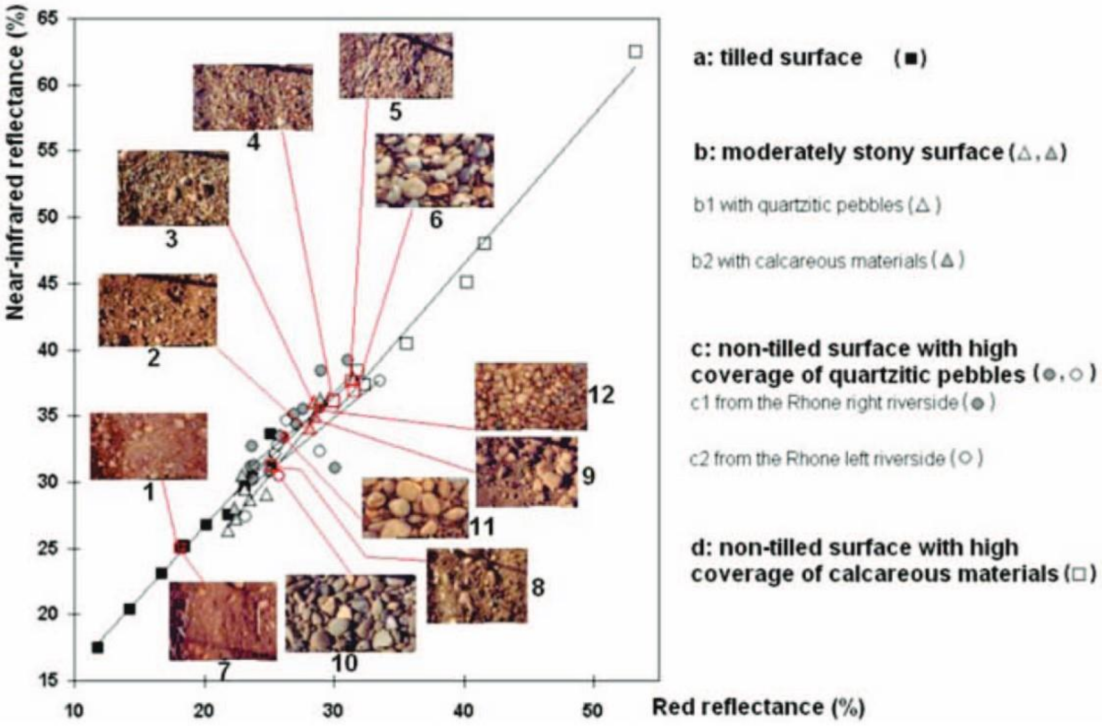
https://www.theia-land.fr

Achievements : soil types

Bayesian Maximum likelihood classification of viticultural soils over the Rhone Valley





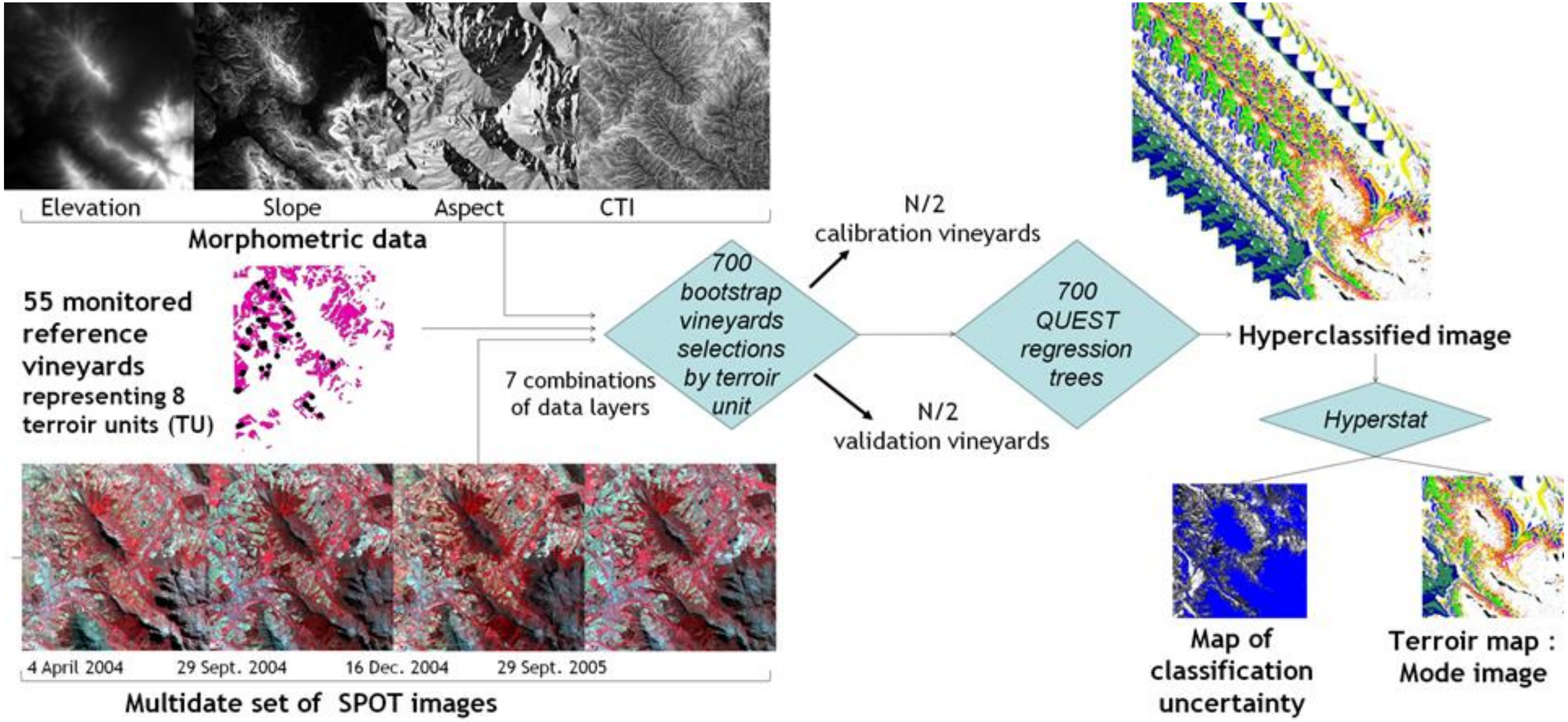


Vaudour, 2008

https://doi.org/10.1080/10106040701207555

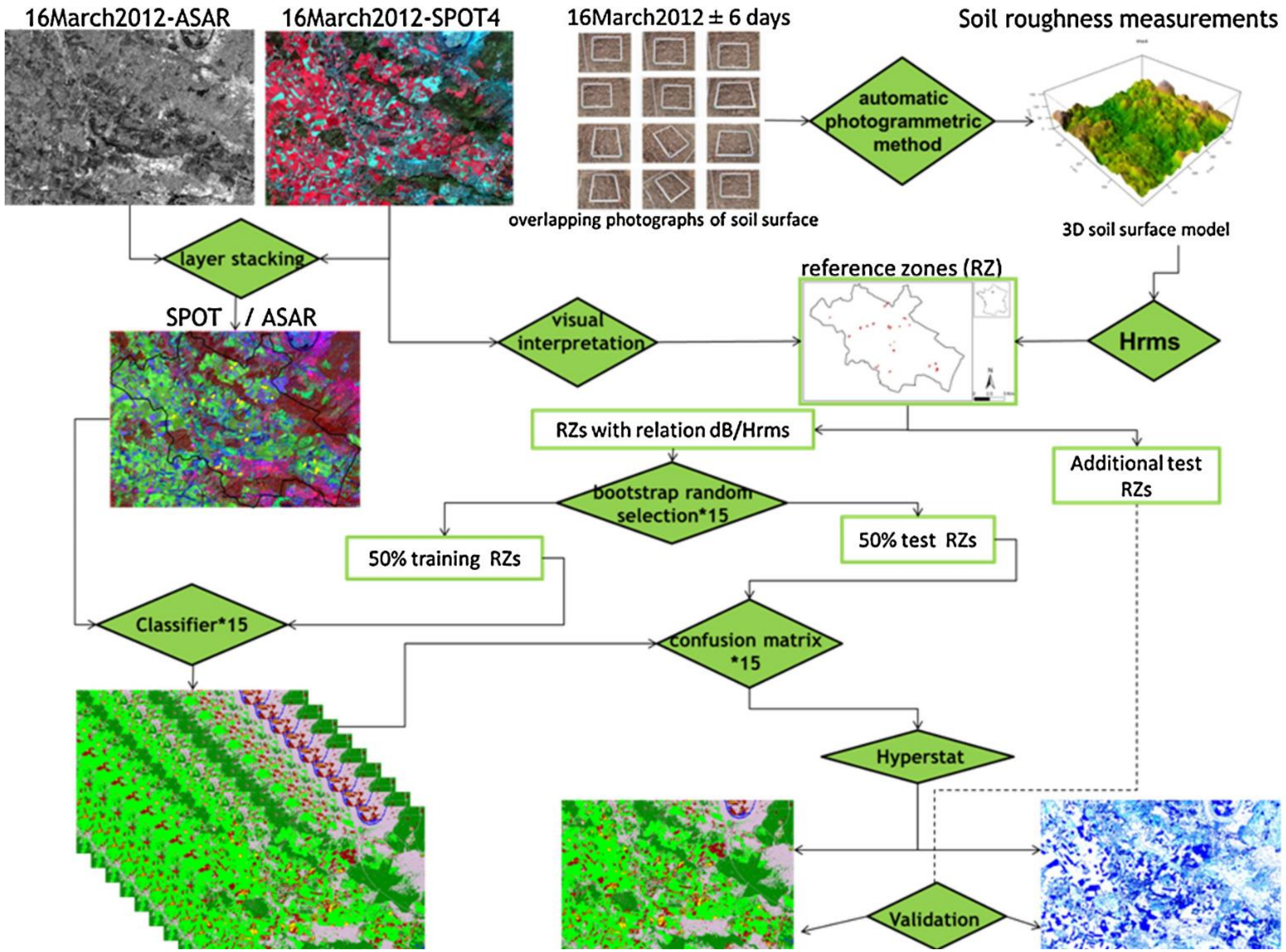
Achievements : homogeneous soil management zones

example of digital viticultural zoning from regression trees

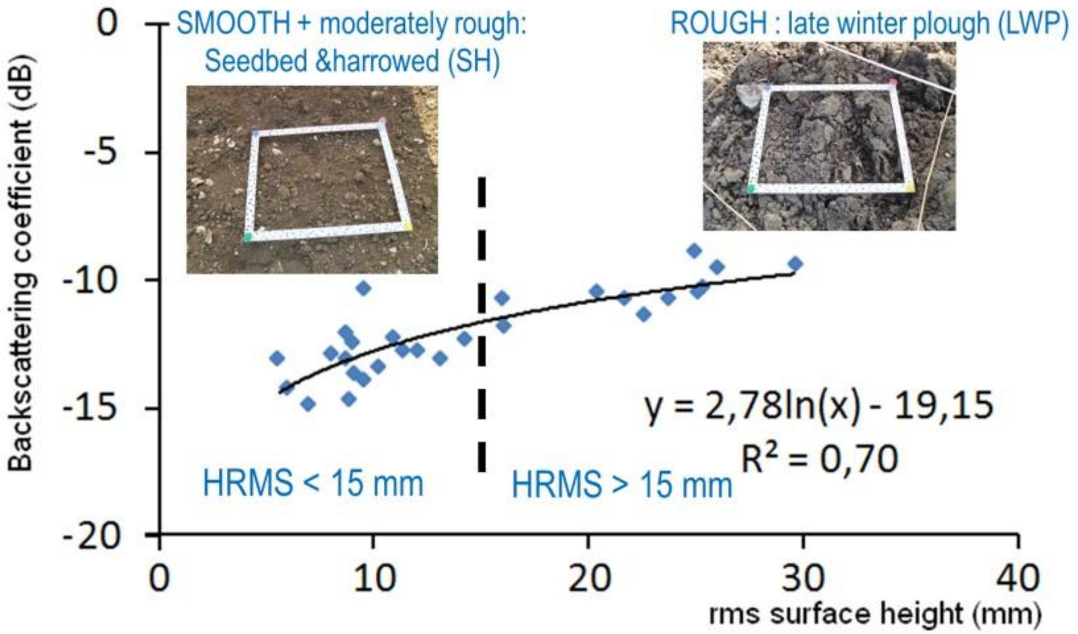


Vaudour et al., 2010
https://doi.org/10.1016/j.rse.2010.08.001

Achievements : identification of soil roughness in order to map soil tillage operations



signal radar (bande C, 5,6 Ghz, polarisation HH)

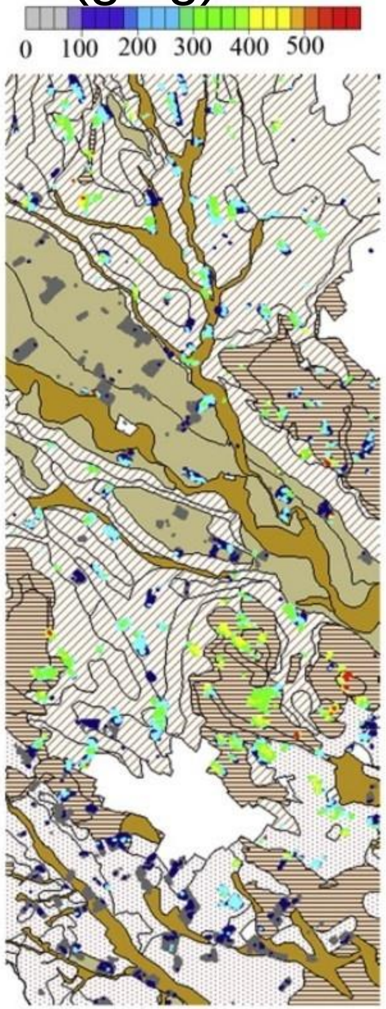


rugosité du sol

Vaudour et al., 2014
https://doi.org/10.1016/j.jag.2013.11.005

Achievements : soil properties
from airborne hyperspectral imagery

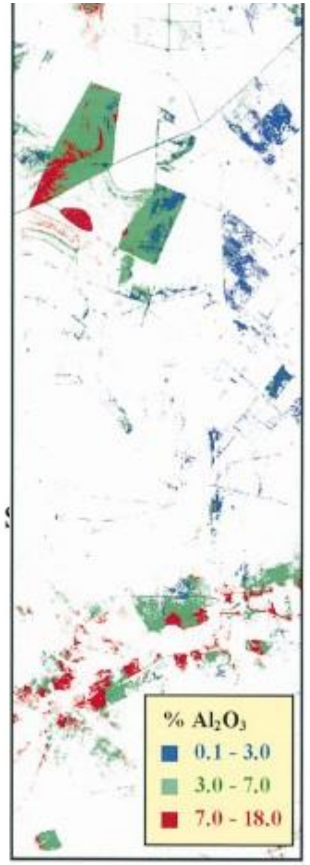
$CaCO_3$ (g/kg)



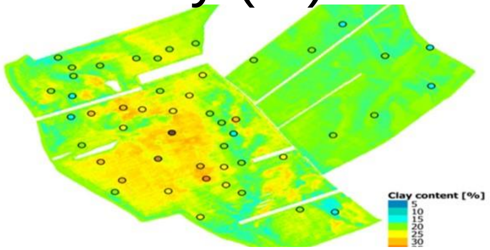
Gomez et al., 2012
https://doi.org/10.1016/j.geoderma.2012.05.023

Al_2O_3 (%) TiO$_2$ (%)

Galvao et al., 2001
https://doi.org/10.1016/S0034-4257(00)00170-X

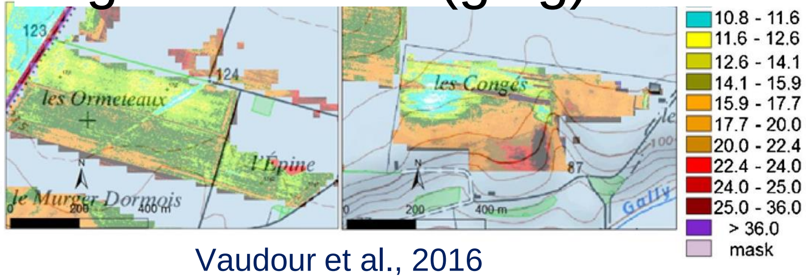


clay (%)



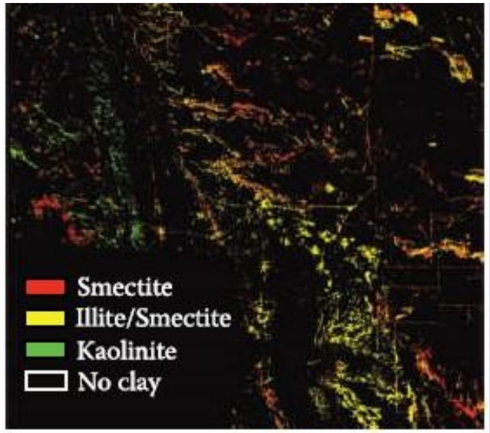
Gholizadeh et al., 2018
https://doi.org/10.1016/j.rse.2018.09.015

organic carbon (g/kg)



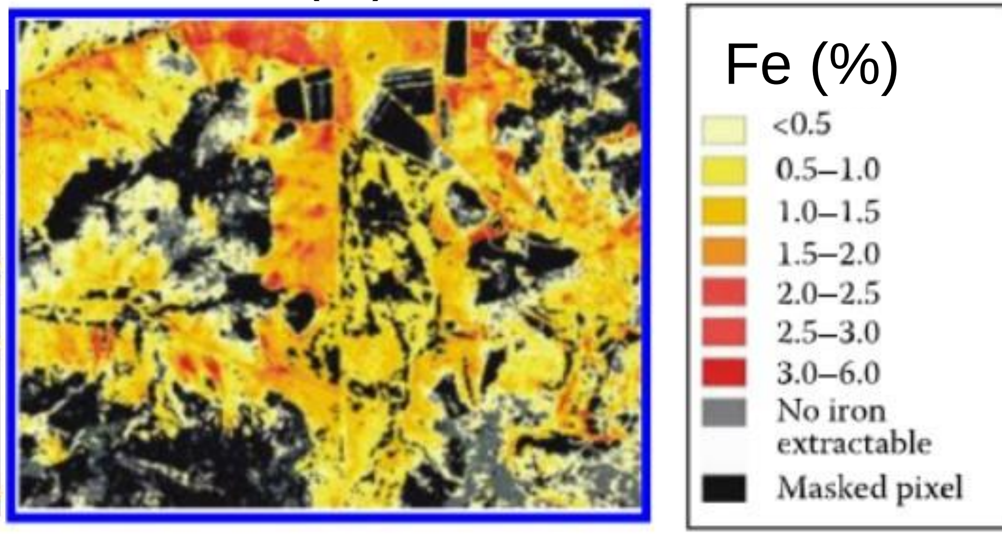
Vaudour et al., 2016
https://doi.org/10.1016/j.jag.2016.01.005

clay minerals



Chabrillat et al., 2002
https://doi.org/10.1016/S0034-4257(02)00060-3

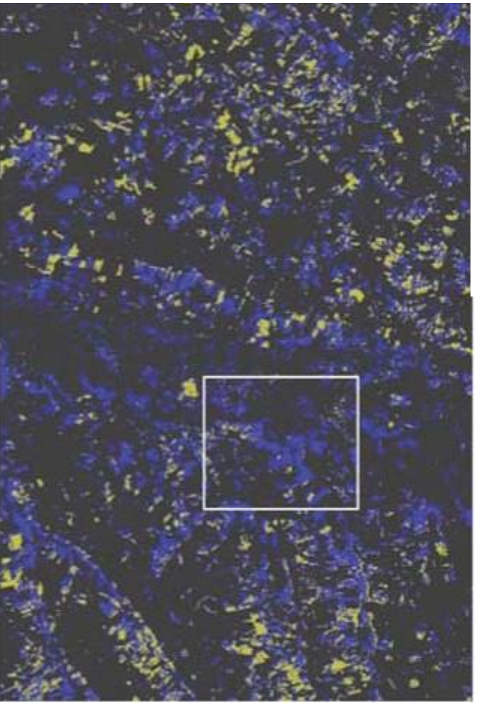
Fe (%)



Richter et al., 2007
https://doi.org/10.2136/sssaj2008.0025

Achievements : soil properties
from single-date multispectral imagery

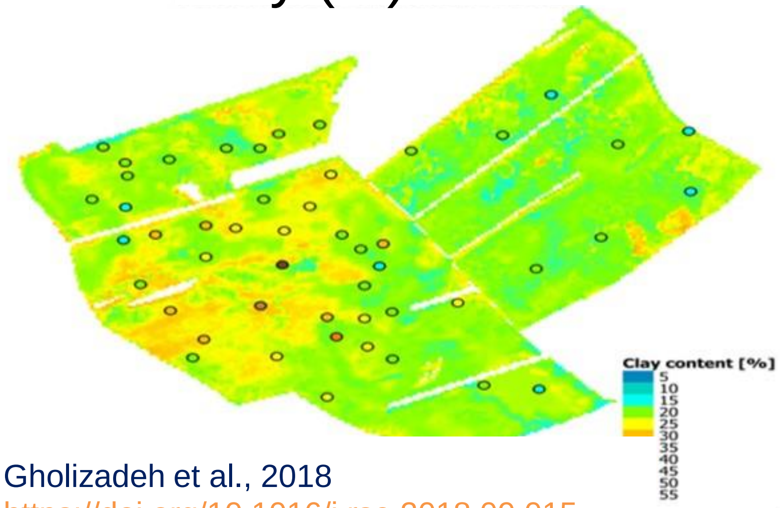
clay minerals



• Illite
• Chlorite

Bourguignon et al., 2007
https://doi.org/10.1144/SP283.10

clay (%)



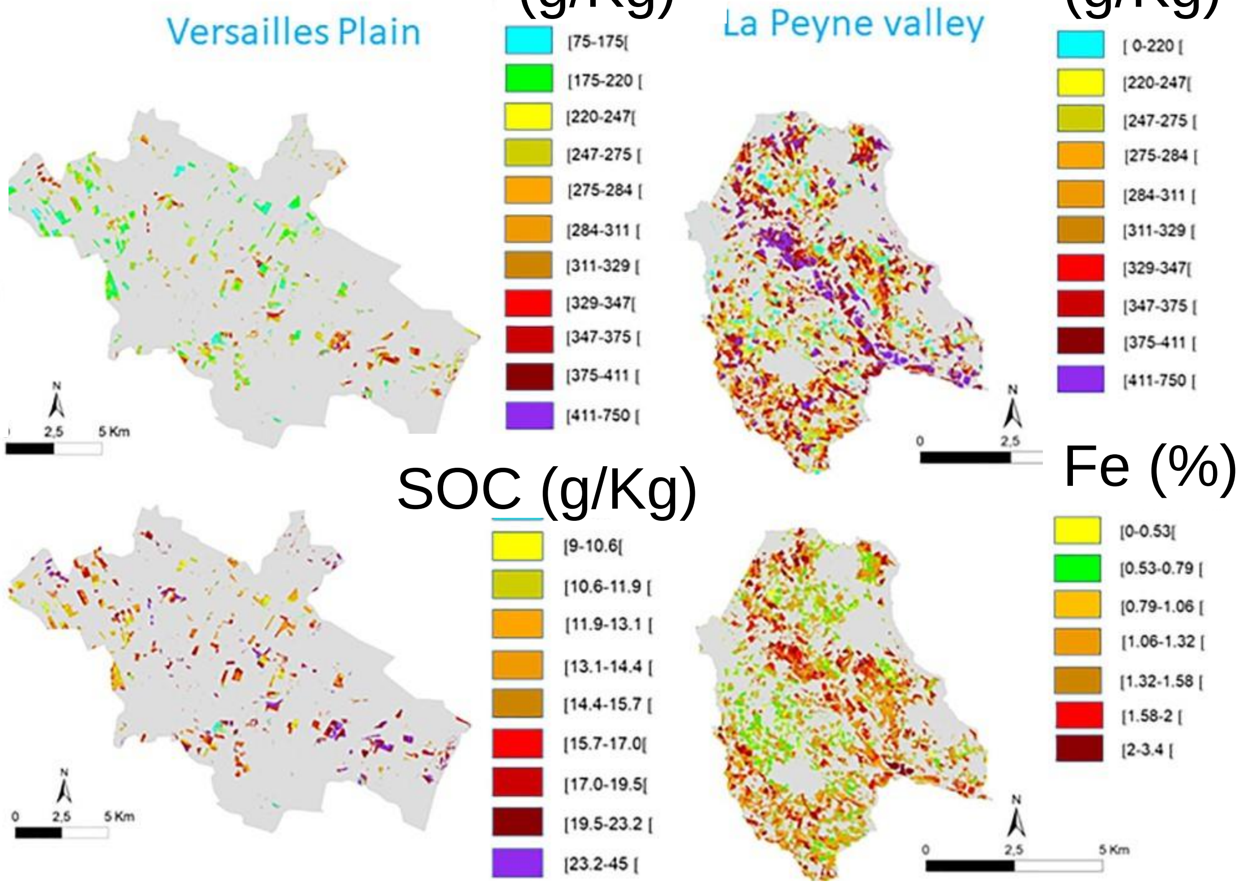
Gholizadeh et al., 2018
https://doi.org/10.1016/j.rse.2018.09.015

SOC (g/Kg)

Castaldi et al., 2019
https://doi.org/10.1016/j.isprsjprs.2018.11.026

clay (g/Kg)

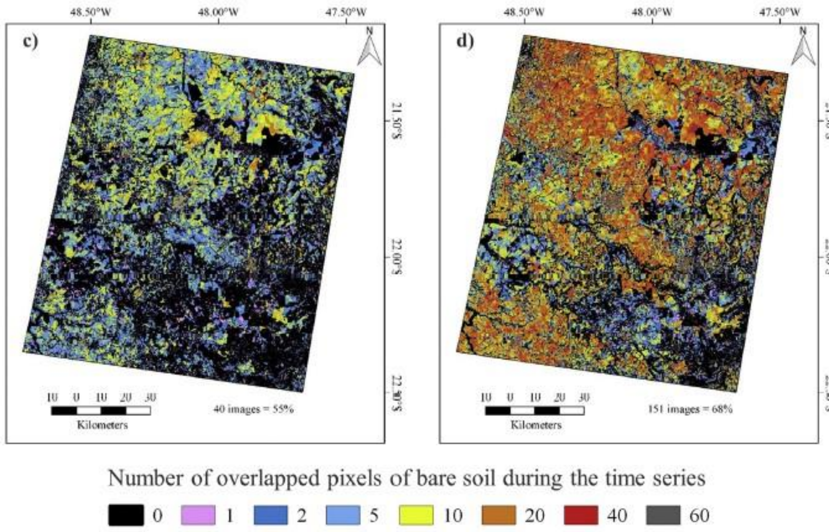
clay (g/Kg)



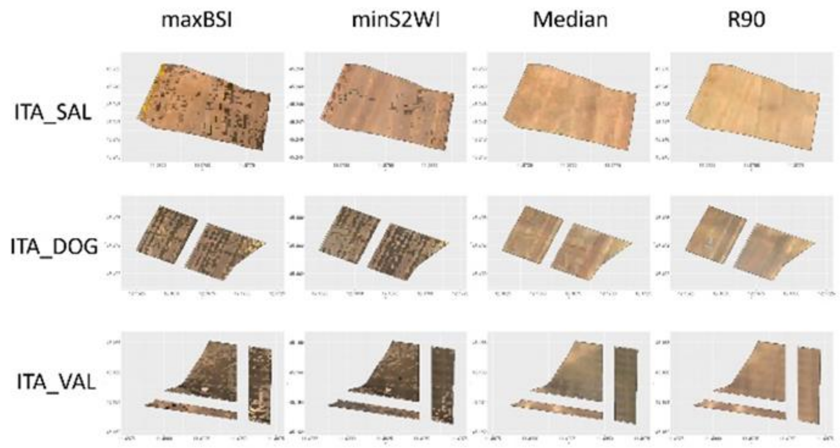
Vaudour et al., 2019
https://doi.org/10.1016/j.rse.2019.01.006

Achievements : bare soil reflectance

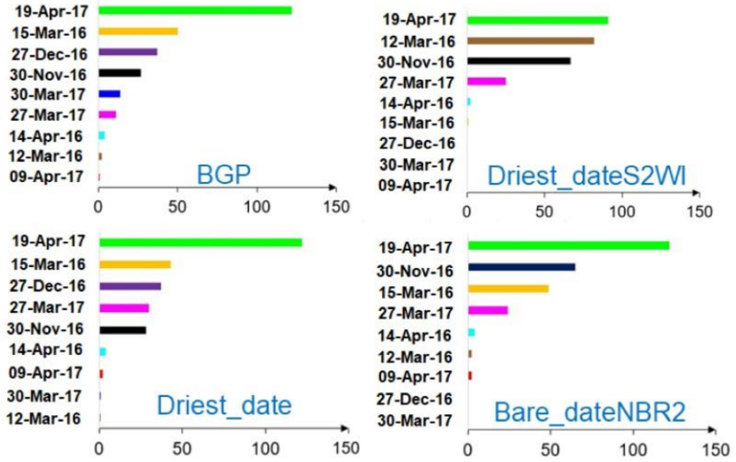
Time scale : temporal mosaic of bare soil



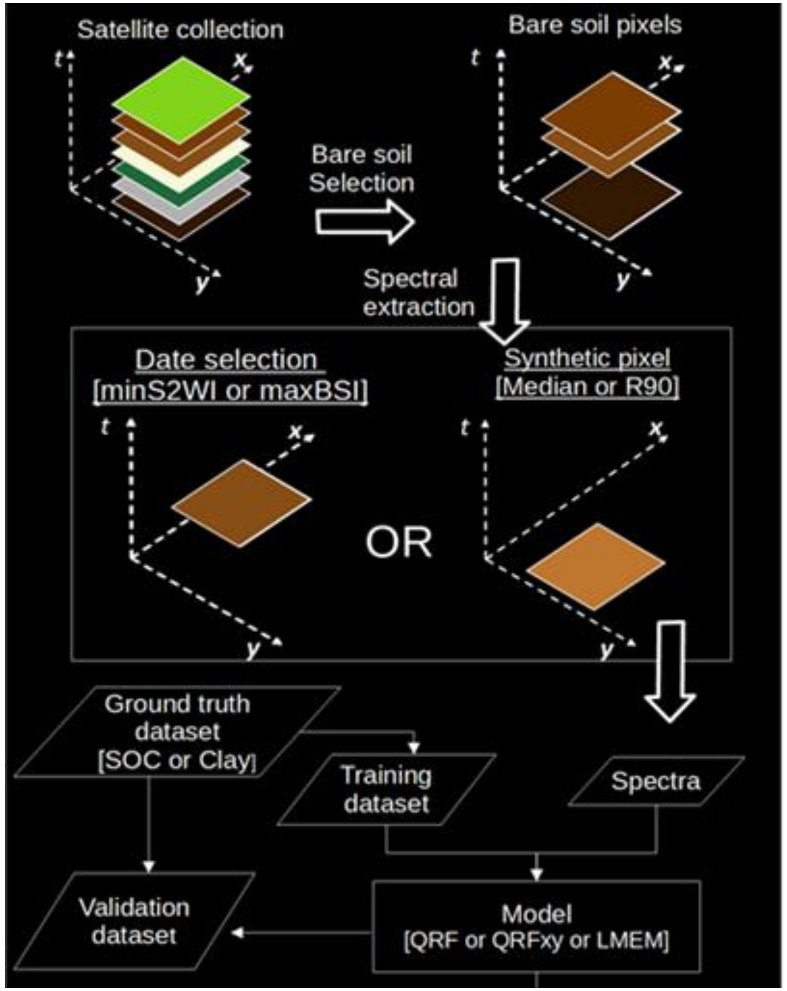
Demattê et al., 2018
https://doi.org/10.1016/j.rse.2018.04.047



Castaldi et al., 2023
https://doi.org/10.1016/j.isprsjprs.2018.11.026



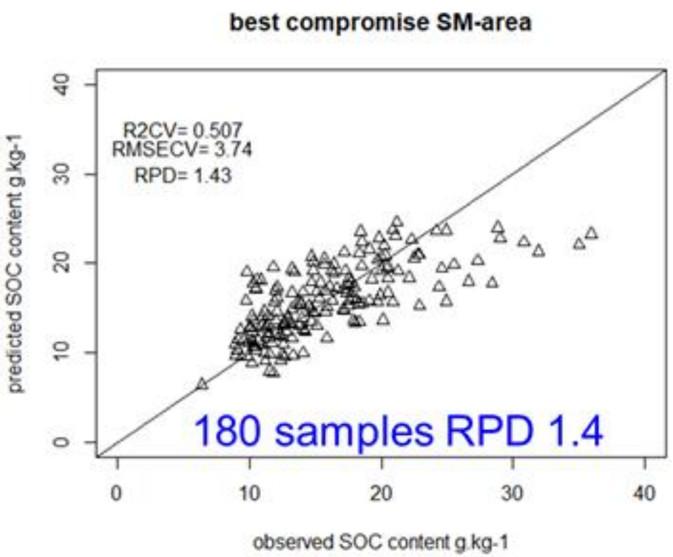
Vaudour et al., 2021
https://doi.org/10.1016/j.jag.2020.102277

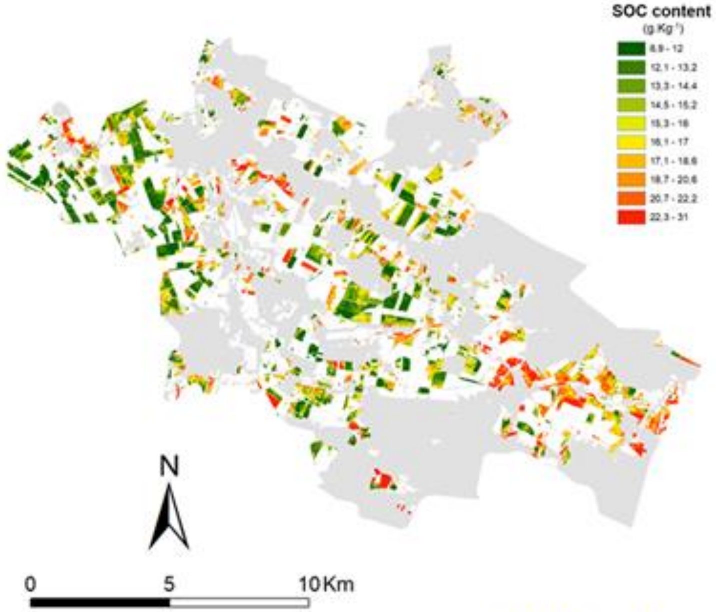


Castaldi et al., 2023
https://doi.org/10.1016/j.isprsjprs.2018.11.026

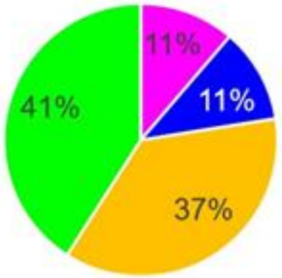
strategies:
-indices thresholding/masking
-per pixel or per date

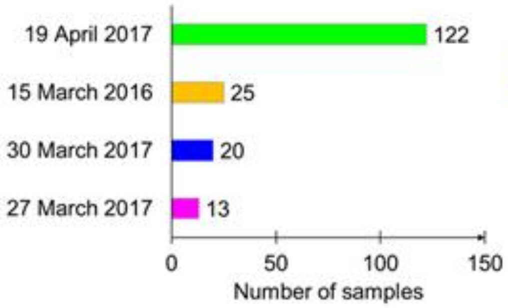
Time scale : temporal mosaic of bare soil



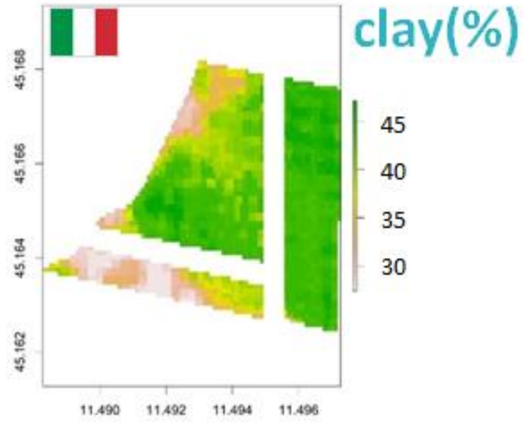


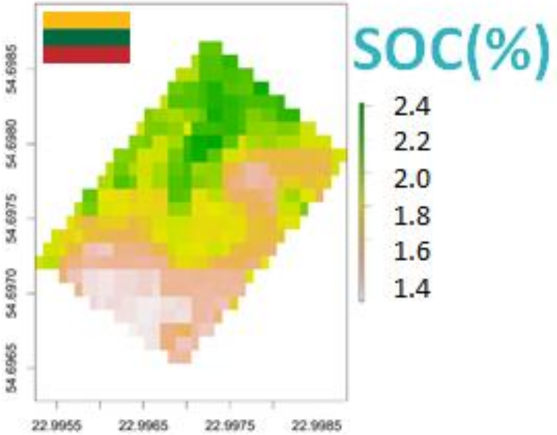
areal distribution





agricultural area predicted *2,44 compared to best single date

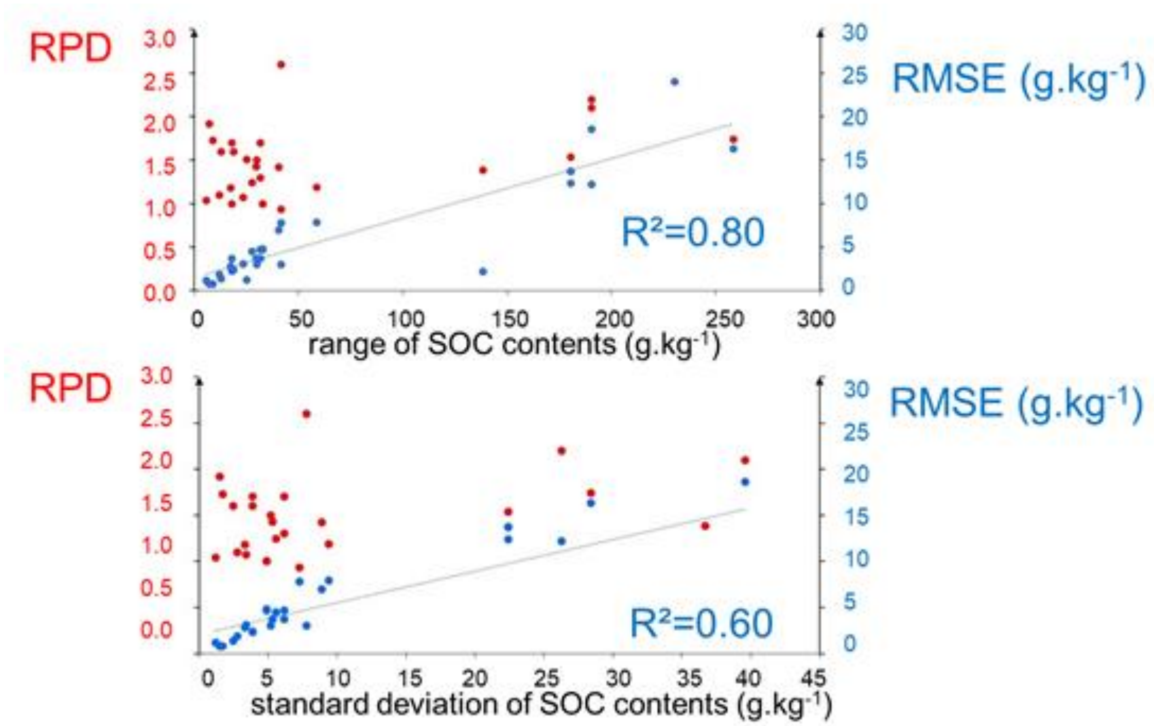




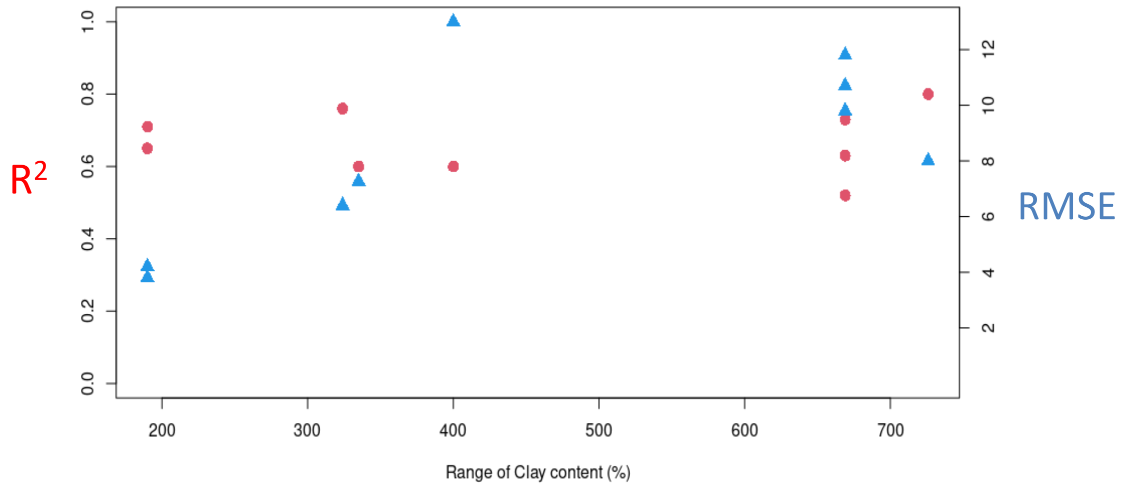
Vaudour et al., 2021
https://doi.org/10.1016/j.jag.2020.102277

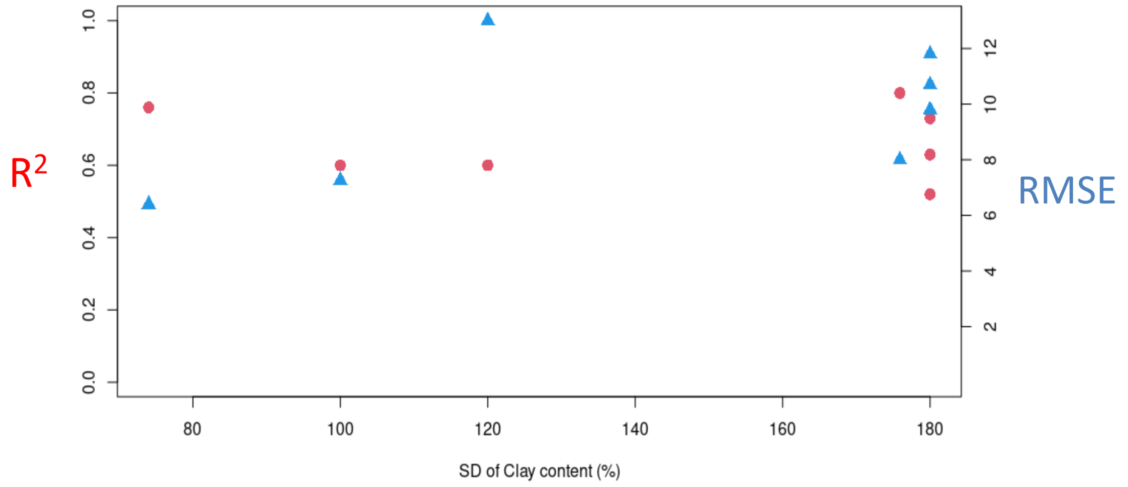
Castaldi et al., 2023
https://doi.org/10.1016/j.isprsjprs.2018.11.026

Huge achievements with huge performances range of estimations



Vaudour et al., 2022
https://doi.org/10.3390/rs14122917

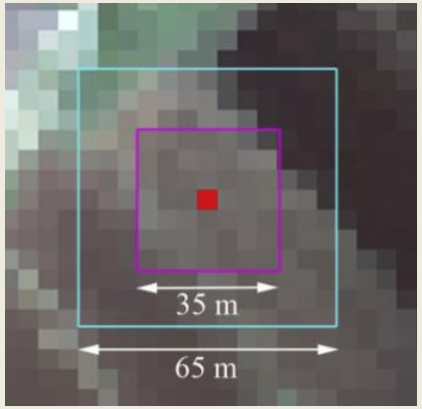


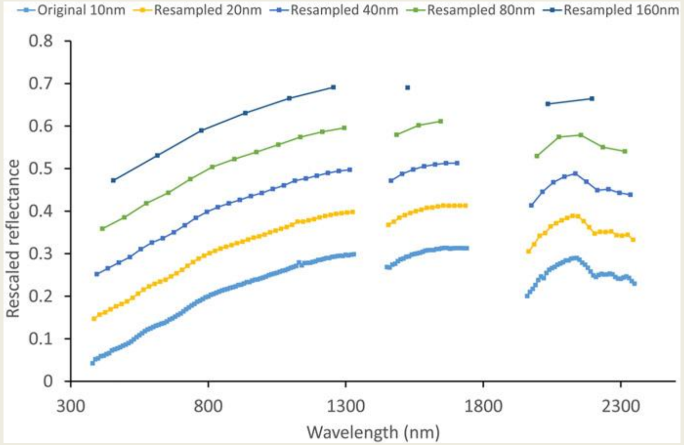


Huge achievements with huge performances range of estimations

Performances depend on instrumental and environmental characteristics

Instrumental characteristics





Castaldi et al., 2016
https://doi.org/10.1016/j.rse.2016.03.025

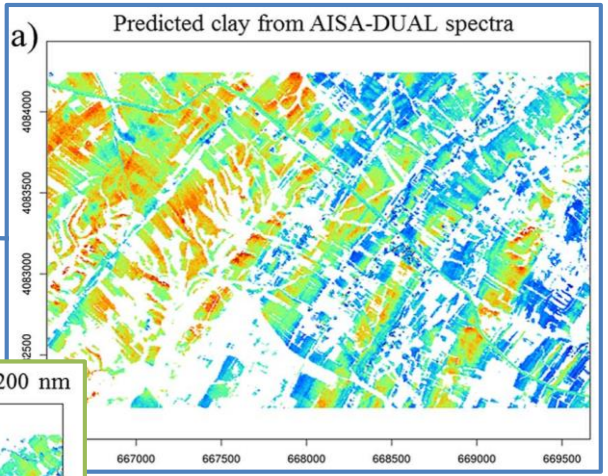
Environmental characteristics

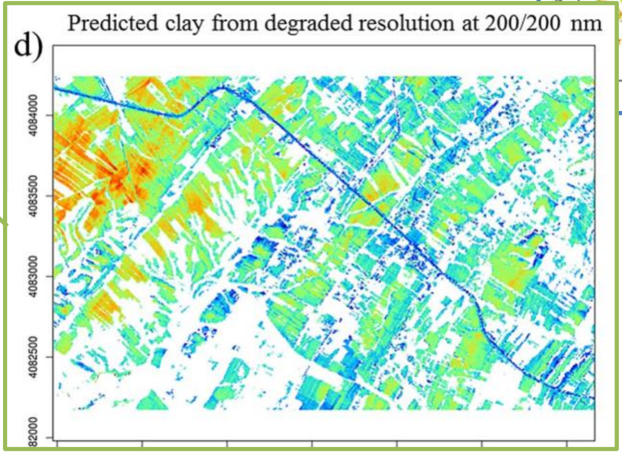
Huge achievements with huge performances range of estimations

Performances depend on instrumental and environmental characteristics

Impact of the spectral resolution on clay prediction

Configuration name	R^2_{cal}	RMSEC (g/kg)	R^2_{val}	RMSEP (g/kg)
AISA-DUAL	0.77	82	0.77	82
~5/10 (EnMAP)	0.73	90	0.78	81
~10/10 (HYPXIM/HyspIRI/HYPERION)	0.75	88	0.73	90
~37/37	0.74	88	0.74	90
~60/60	0.75	85	0.71	93
~100/100	0.75	87	0.71	94
~200/200	0.35	139	0.01	173





Adeline et al., 2018
http://dx.doi.org/10.1016/j.geoderma.2016.11.010

Gomez et al., 2018
https://doi.org/10.1016/j.rse.2017.10.047

Huge achievements with huge performances range of estimations

Performances depend on instrumental and environmental characteristics

Impact of the atmospheric correction model on clay prediction

		S2 acquisition date (DD-MM-YYYY)			
		03-02-2017	16-02-2017	23-02-2017	26-02-2017
MAJA	R^2_{cv}	0.62	0.63	0.62	0.61
Sen2Cor	R^2_{cv}	0.62	0.63	0.62	0.60
LaSRC	R^2_{cv}	0.63	0.62	0.62	0.59

Huge achievements with huge performances range of estimations

Performances depend on instrumental and environmental characteristics

Impact of the surface conditions on clay prediction

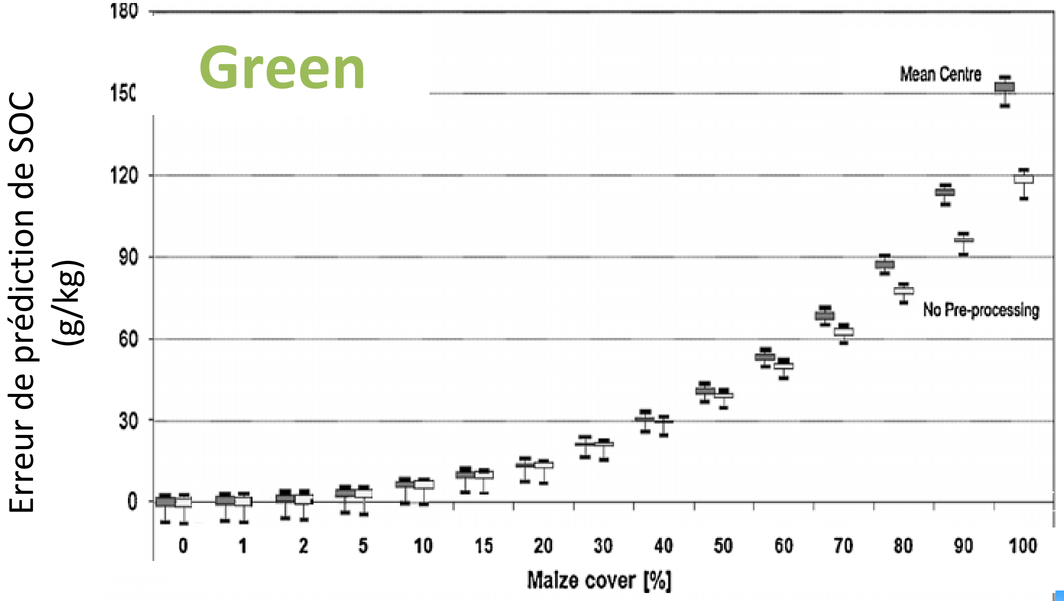
		S2 acquisition date (DD-MM-YYYY)										
		03-02-2017	16-02-2017	23-02-2017	26-02-2017	08-03-2017	25-03-2017	28-03-2017	04-04-2017	24-04-2017	27-04-2017	07-05-2017
MAJA	R^2_{cv}	0.62	0.63	0.62	0.61	0.52	0.74	0.71	0.62	**0.80**	0.73	0.72
Sen2Cor	R^2_{cv}	0.62	0.63	0.62	0.60	0.50	0.76	0.72	0.62	**0.80**	0.74	0.72
LaSRC	R^2_{cv}	0.63	0.62	0.62	0.59	0.50	0.75	0.72	0.63	**0.77**	0.72	0.68

Gomez et al., 2021
https://doi.org/10.1016/j.geoderma.2022.115959

Huge achievements with huge performances range of estimations

Performances depend on instrumental and environmental characteristics

Impact of the vegetation on SOC prediction



Bartholomeus et al., 2011
https://doi.org/10.1016/j.jag.2010.06.009

Huge achievements with huge performances range of estimations

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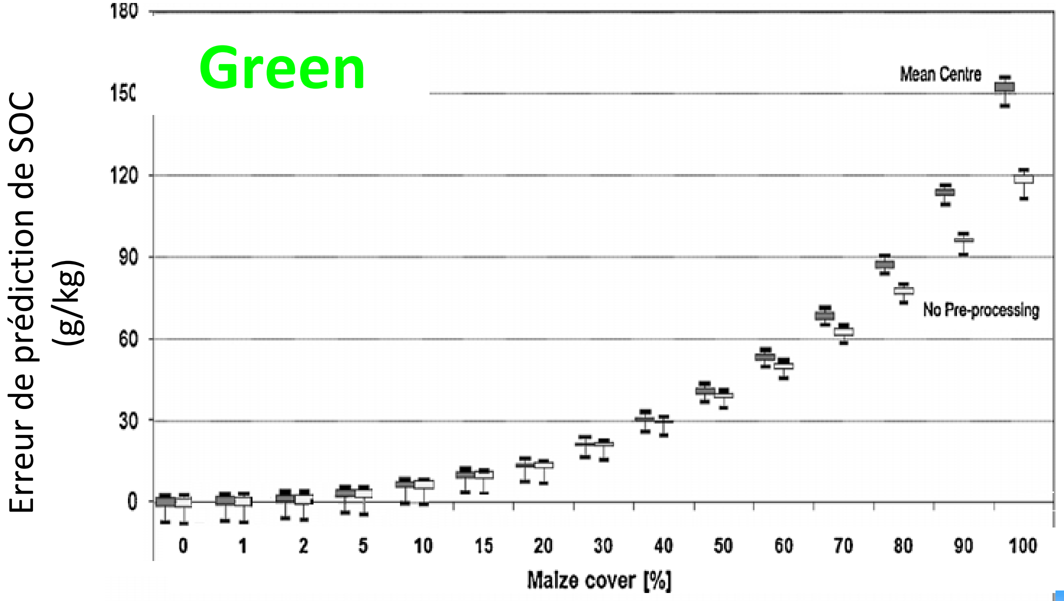
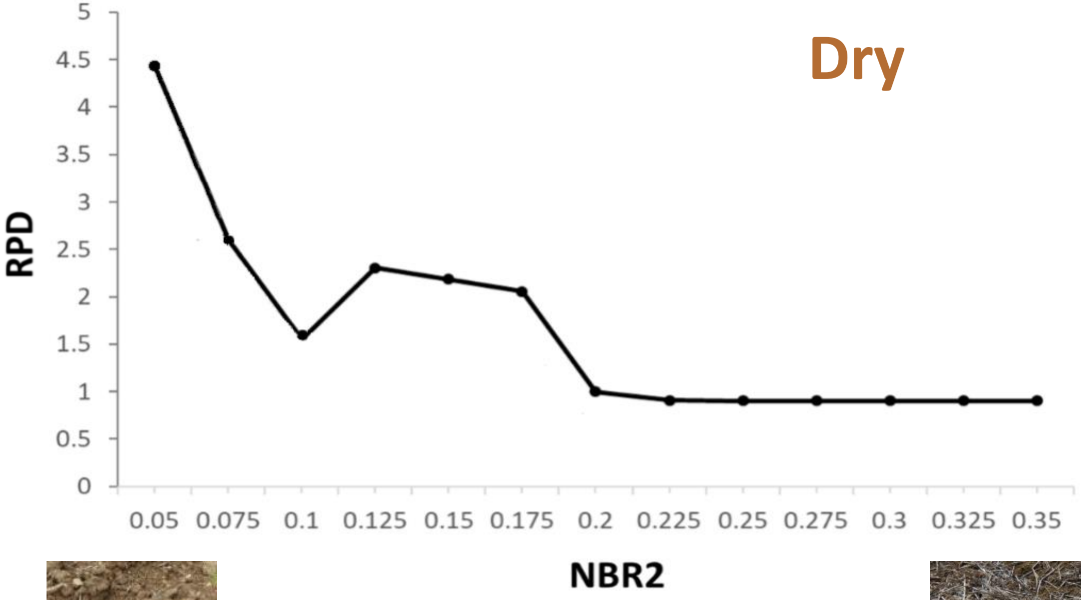
Impact of the vegetation on SOC prediction





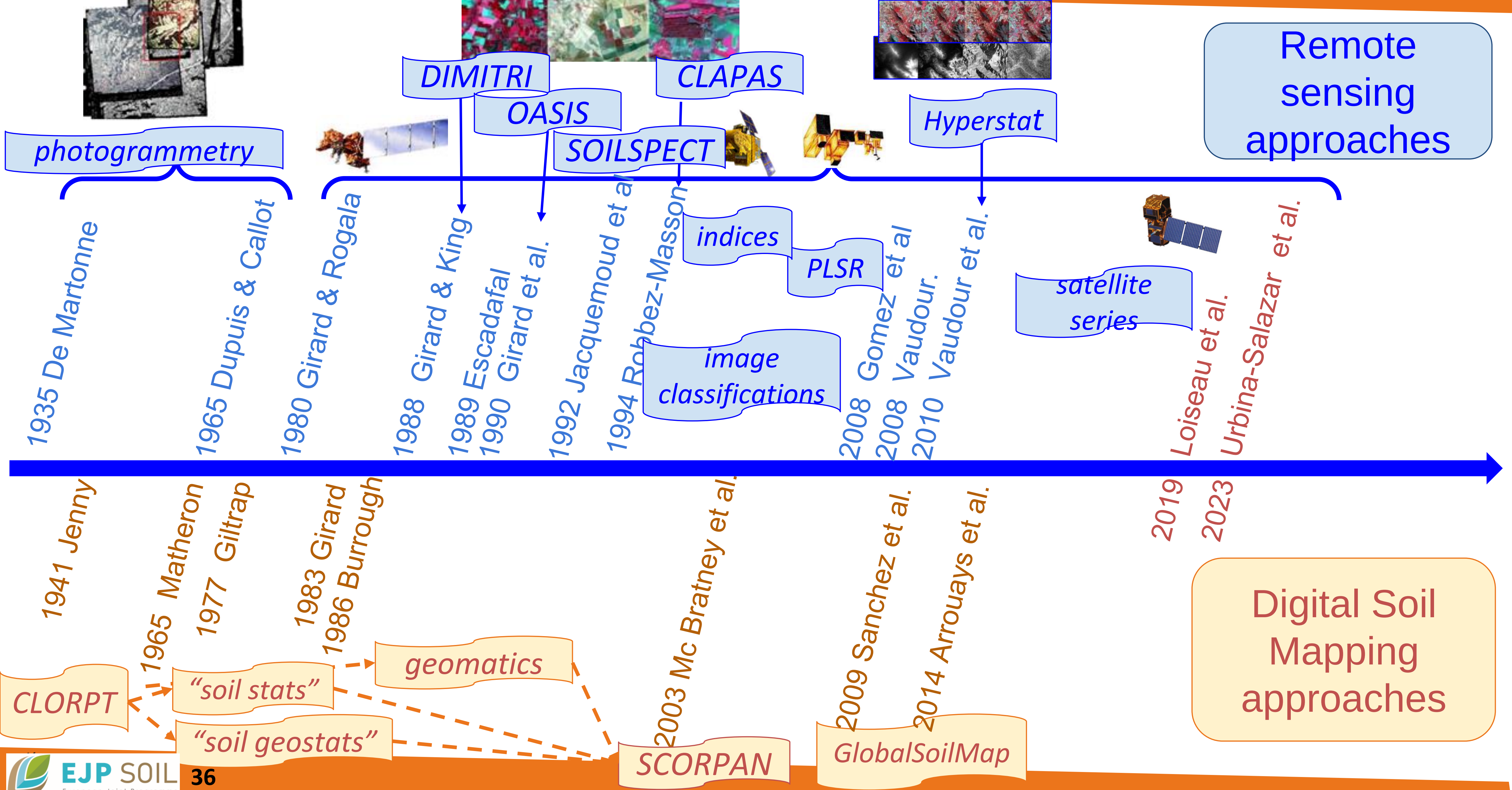




Bartholomeus et al., 2011
https://doi.org/10.1016/j.jag.2010.06.009

Castaldi et al., 2019
https://www.mdpi.com/2072-4292/11/18/2121

Towards the integration of remote sensing data into digital soil mapping approaches



EJP SOIL European Joint Programme

Digital Soil Mapping

$$\text{Soil} = f(S, C, O, R, P, A, N) + \varepsilon$$

Spatial inference models

Soil

Climate

Organisms

Relief

Parent material

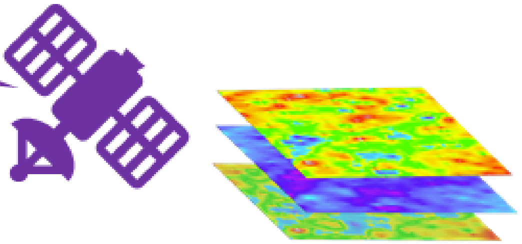
Age

Location XY

Estimated error

- Legacy soil data (soil profiles, soil maps)
- Soil sensing

Spatial data on the determinants of soil variability or correlated to this variability (covariates)

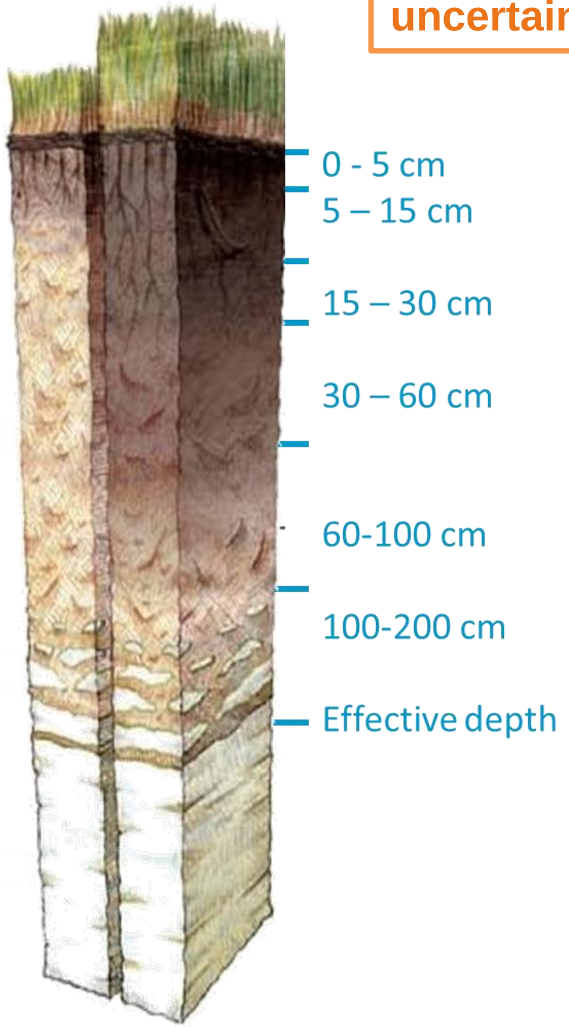


Soil property prediction maps (from the World to the plot) + quantification of uncertainty

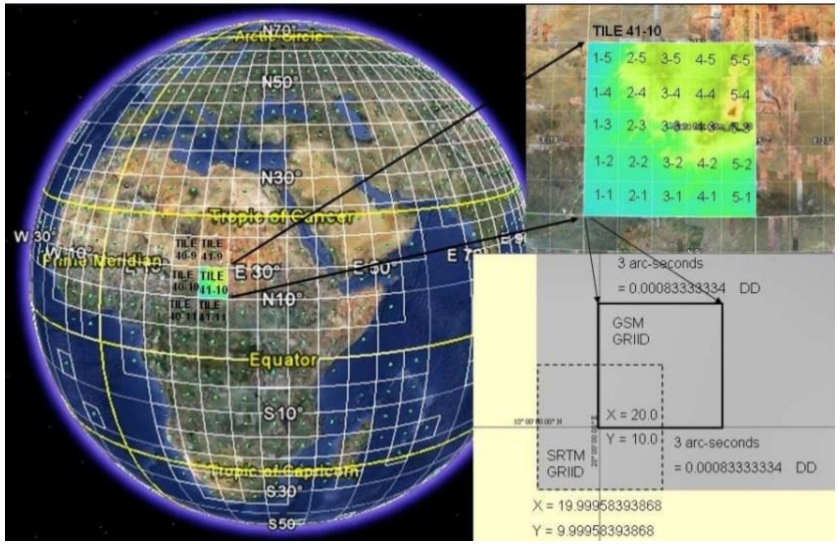
McBratney *et al.*, 2003
https://doi.org/10.1016/S0016-7061(03)00223-4

GlobalSoilMap

Deliver a digital database of soil properties around the world, measuring 90x90m, along with their uncertainties, freely downloadable

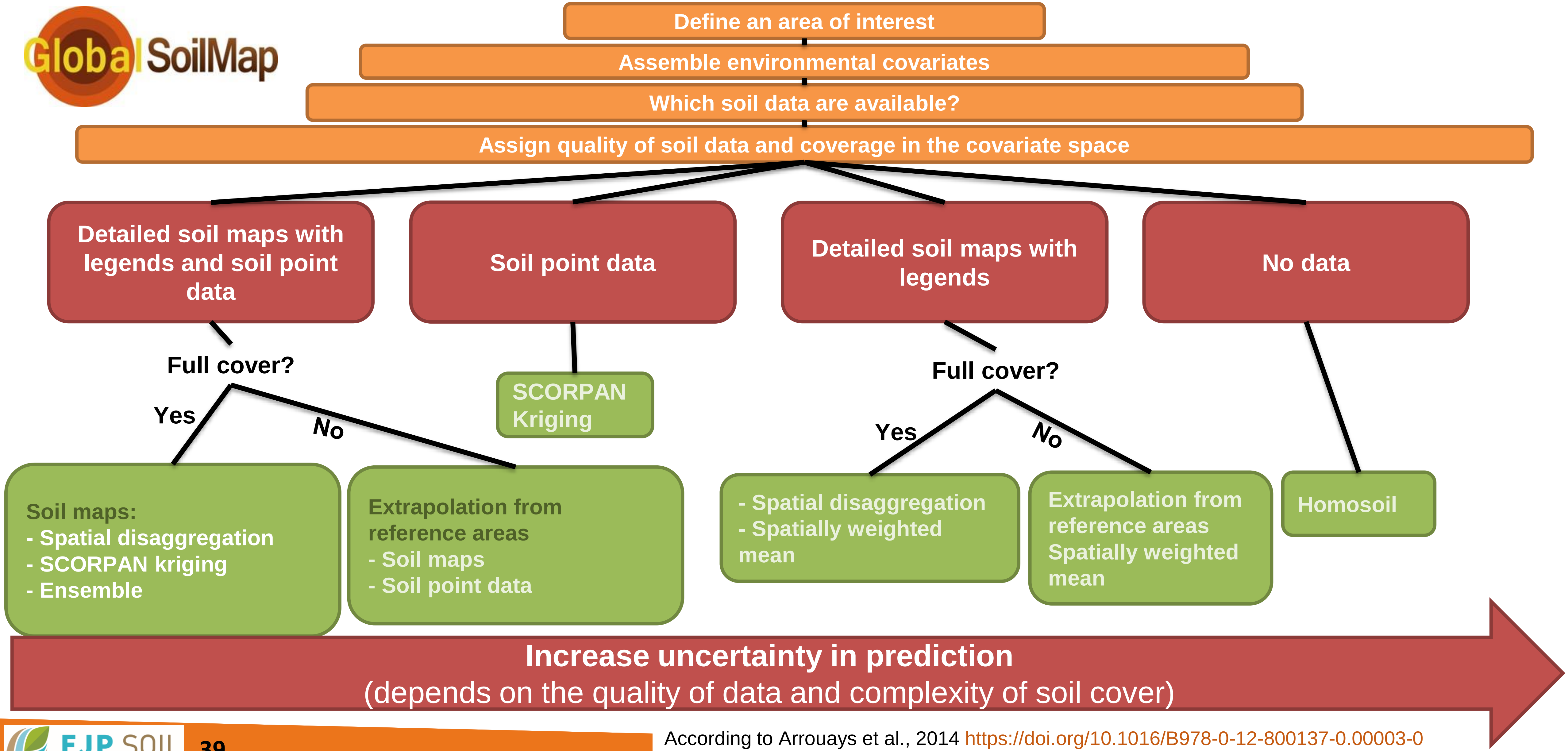


- **Fitted to the SRTM -90-m grid**
- **Whole world**
- **18 billion points and blocks (66.5 M in France)**
- **Point and cell prediction**
- **Quantified properties**
- **Essential for modeling in space and time**



- **Scalable with the integration of new data or new methods**
- **Easier to harmonize than conventional cards**
- **Easy to cross-reference with other sources of spatial information**

GlobalSoilMap global program specifications



According to Arrouays et al., 2014 https://doi.org/10.1016/B978-0-12-800137-0.00003-0
and an initial diagram by Minasny and McBratney, 2010 https://doi.org/10.1007/978-90-481-8863-5_34

Remote sensing data used as covariates in *SCORPAN* model

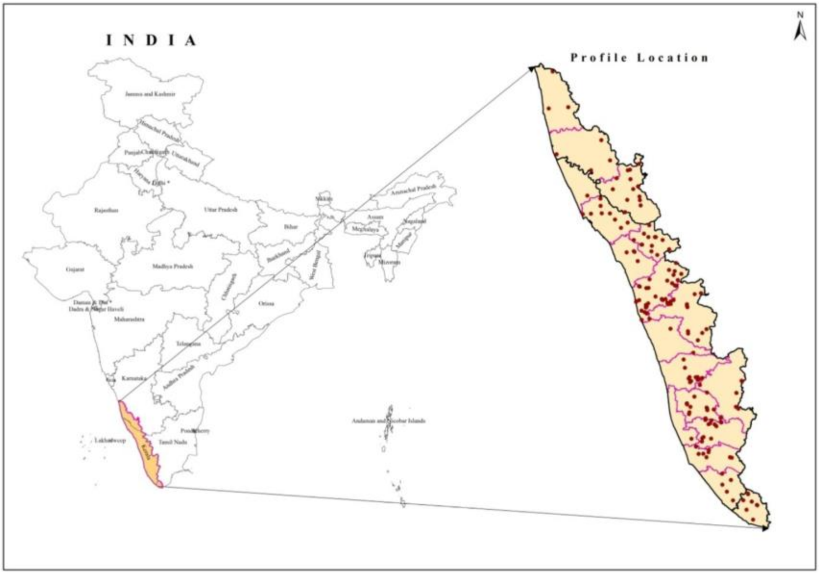
Table 3
Summary, in chronological order, of previous quantitative scorpan-like studies in which soil classes and/or attributes were spatially predicted

Soil S_{class}	Soil $S_{attribute}$	Predictive model (f)	Predictive factors s	c	o	r	p	a	n	Study area spatial extent	No. of observations	Grid distance (m) Soil sample	Grid distance (m) Image	Location	Authors
Soil drainage classes		Linear regression				×				D3				USA	Troeh (1964)
	Soil horizon thickness, subsoil mottle, depth to mottle	Linear regression				×				D1	90		10	USA	Walker et al. (1968)
Soil classes		Discriminant analysis	×							D3	30	1000		USA	Pavlik and Hole (1977)
Soil classes	Degree of podzolisation	Modified principal component analysis (Escoufier, 1970)				×	×			D4	38		500	France	Legros and Bonneric (1979)
	Thickness of A horizon, depth to $CaCO_3$	Discriminant analysis, linear regression				×				D2	522	10, 50	10, 50	Canada	Pennock et al. (1987)
Soil classes		Clustering	×			×				D2				USA	Lee et al. (1988)
	Organic C, Fe/C	Clustering and regression			×					D2	32			USA	Frazier and Cheng (1989)
	Organic C, P	Regression, kriging			×				×	D2	172	15	15	USA	Bhatti et al. (1991)
	Soil morphological, physical and chemical properties	Ordination techniques	×			×				D2	194	2, 8	10	Australia	Odeh et al. (1991)
Soil classes			×			×				D2	194	2, 8	10	Australia	Odeh et al. (1992)
Soil drainage classes		Discriminant analysis				×	×			D3	305			USA	Bell et al. (1992, 1994)
	Clay content, CEC, EC, pH, bulk density, COLE, θ at −10 and −1500 kPa	Ordination, GLM				×	×			D3	224	300	100	Lower Macquarie Valley, Australia	McKenzie and Austin (1993)

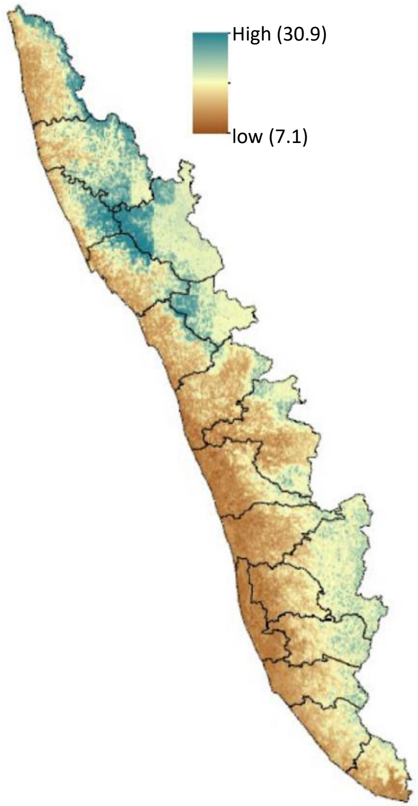
McBratney et al., 2003
https://doi.org/10.1016/S0016-7061(03)00223-4

Remote sensing data used as covariates in *SCORPAN* model

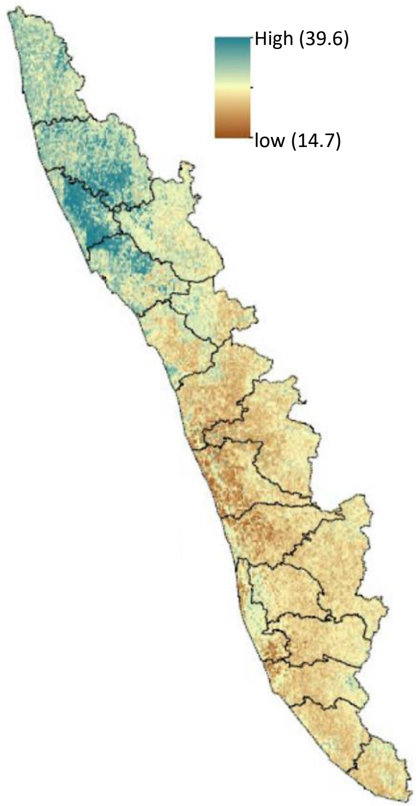
Soil organic carbon (SOC) Stock mapping



Predicted total SOC Stock



Uncertainty estimates of SOC Stock



Model covariates:

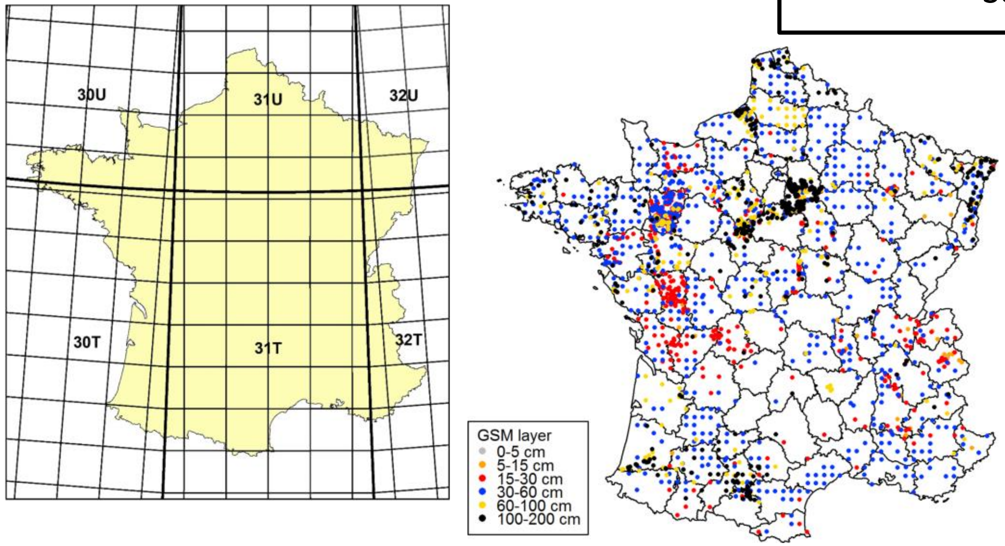
- “Classic” covariates:
    - Derivatives of digital elevation model (DEM)
    - Normalized Difference Vegetation Index (NDVI)
    - Enhanced vegetation index (EVI)

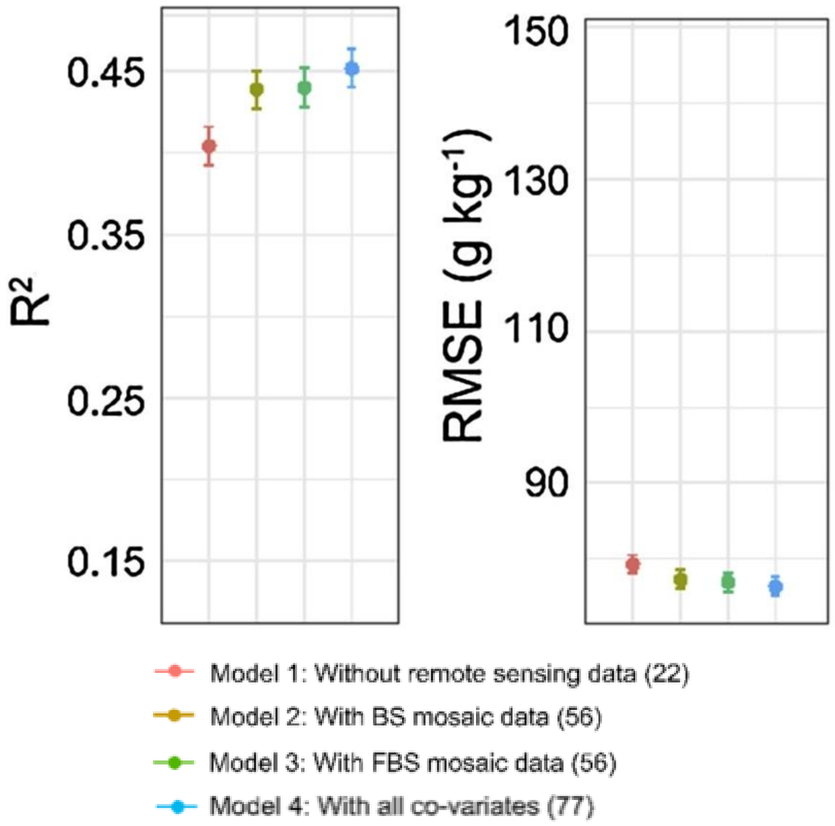
- + all bands of Landsat-8 imagery (11 bands)

Dharumarajan et al., 2021
https://doi.org/10.1016/j.geodrs.2021.e00387

Remote sensing data used as covariates in *SCORPAN* model

Soil clay content mapping





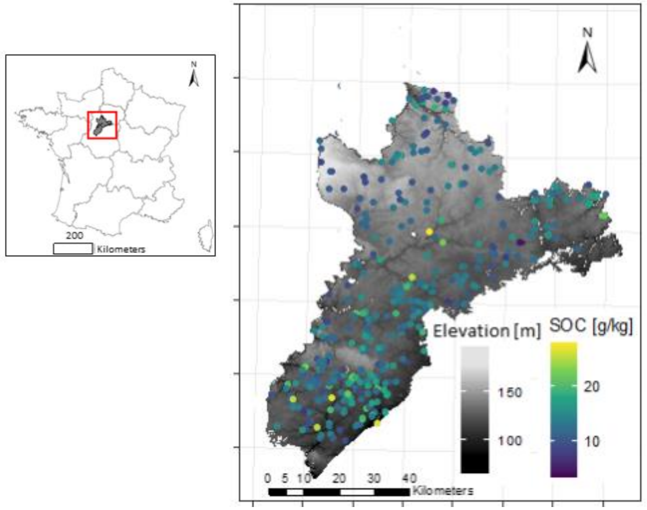
Model covariates:

- “Classic” covariates: derivatives of DEM, NDVI, Land use map, and climate, geology, topography, and soil information…

- + 11 spectral indices calculated from Sentinel-2 mosaics, based on images close to sowing periods (Mars & Dec) in 2016-2017.

Loiseau et al., 2019
https://doi.org/10.1016/j.jag.2019.101905

Remote sensing data used as covariates in *SCORPAN* model



Soil organic carbon content mapping

RS models	R^2
Test_1	0.18
Test_2	0.19
Test_3	0.11

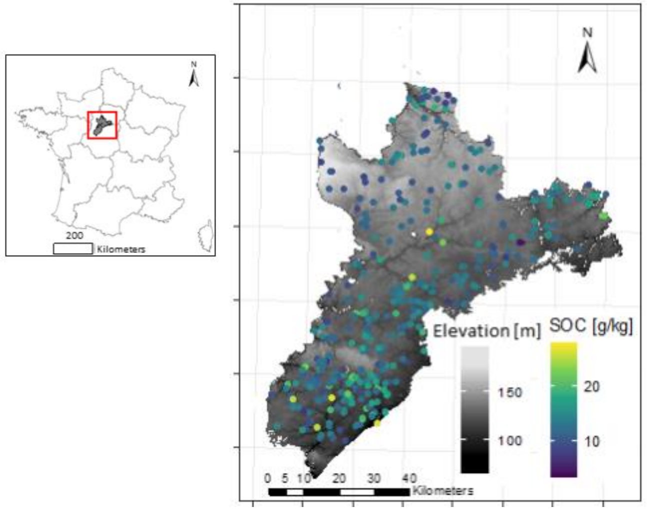
Model covariates:

- "Classic" covariates: derivatives of DEM,position and parent material.

- + Bare Soil Temporal Mosaic based on:
    - Test_1 : all S2 images (2016 -2021)
    - Test_2 : S2 images between February and May (2016-2021)
    - Test_3 : S2 images between July and November (2016-2021)

Urbina-Salazar et al., 2023
https://doi.org/10.3390/rs15092410

Remote sensing data used as covariates in *SCORPAN* model



Soil organic carbon content mapping

RS models	R^2	DSM Models	R^2
Test_1	0.18	+ "Classic" covariates : derivatives of DEM,position and parent material	0.26
Test_2	0.19		**0.33**
Test_3	0.11		0.27

Model covariates:

- "Classic" covariates: derivatives of DEM,position and parent material.

- \+ Bare Soil Temporal Mosaic based on:
  - Test_1 : all S2 images (2016 -2021)
  - Test_2 : S2 images between February and May (2016-2021)
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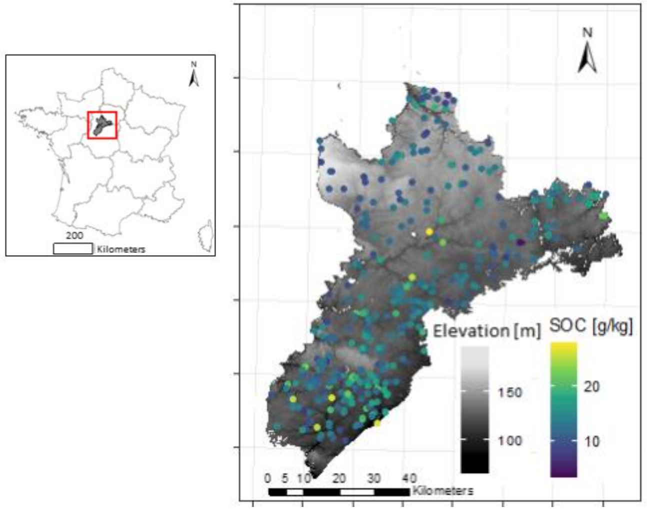
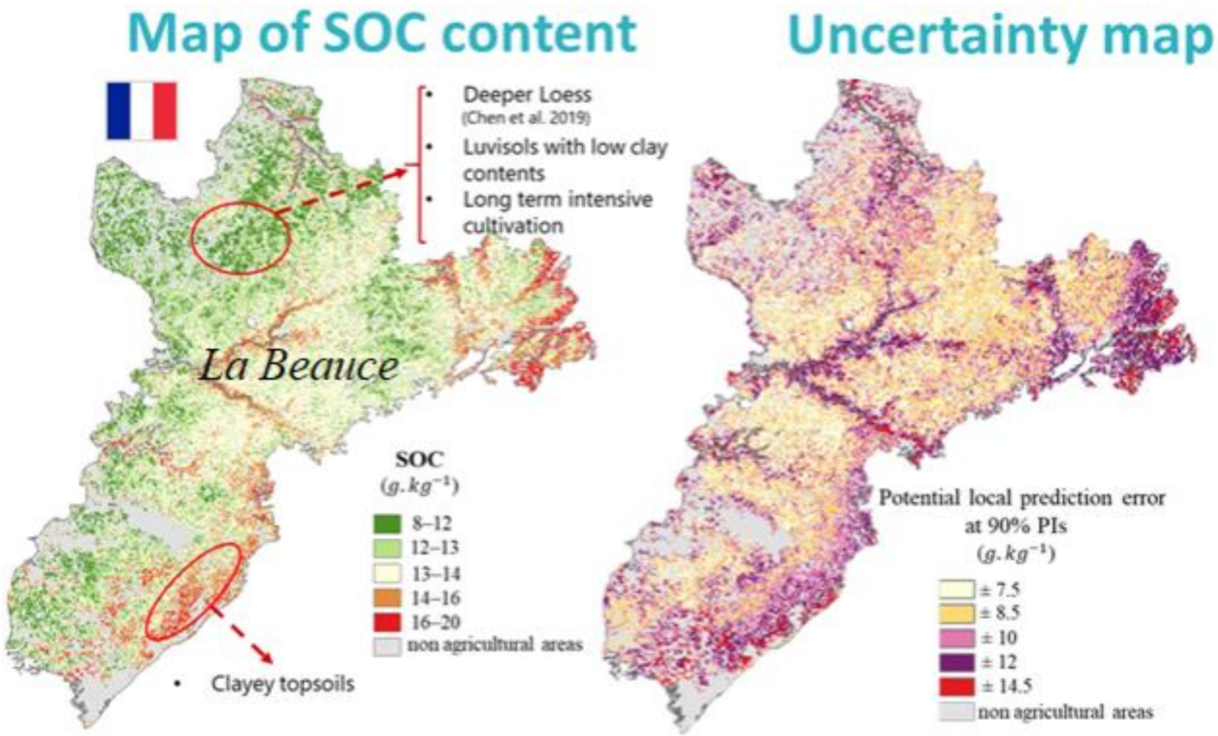
Remote sensing data used as covariates in *SCORPAN* model



Soil organic carbon content mapping



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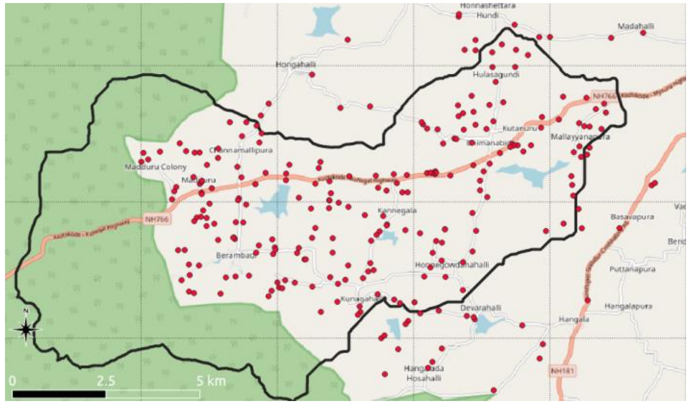
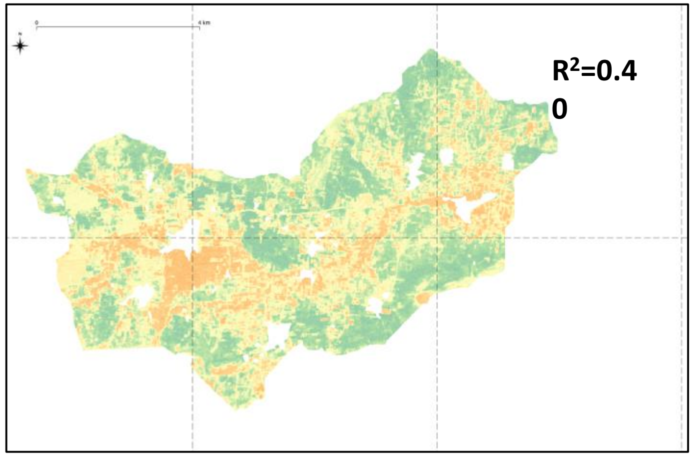
Urbina-Salazar et al., 2023
https://doi.org/10.3390/rs15092410

Mapping soil clay content by training Digital Soil Mapping models with surrogate measurements obtained from Sentinel-2 data

Soil clay content mapping





Model covariates:

- “Classic” covariates: derivatives of DEM & NDVI.
- + all bands of Sentinel-2 imagery (10 bands)

Weerasekara et al., Soumis

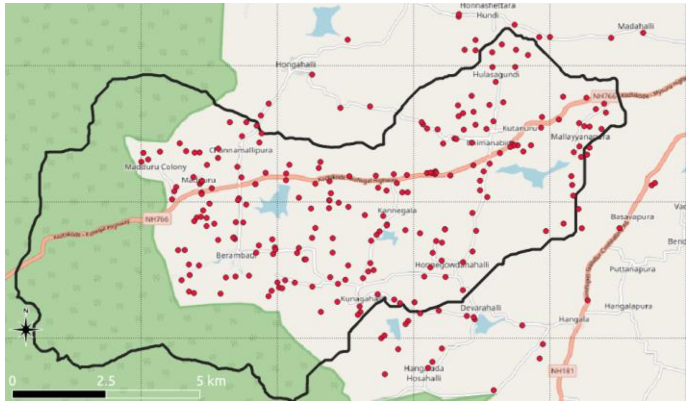
Mapping soil clay content by training Digital Soil Mapping models with surrogate measurements obtained from Sentinel-2 data

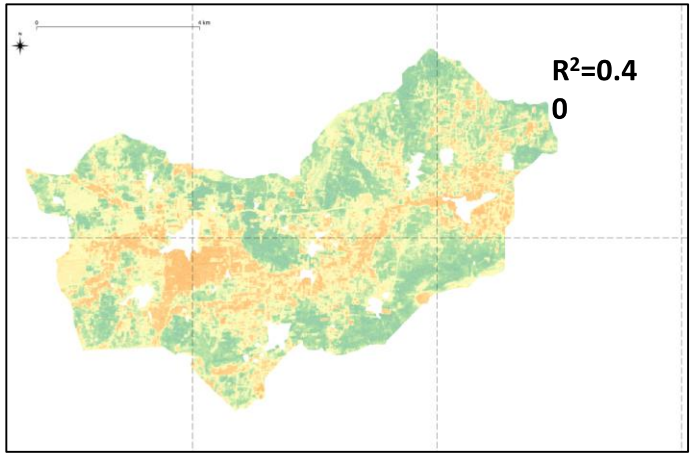
Soil clay content mapping

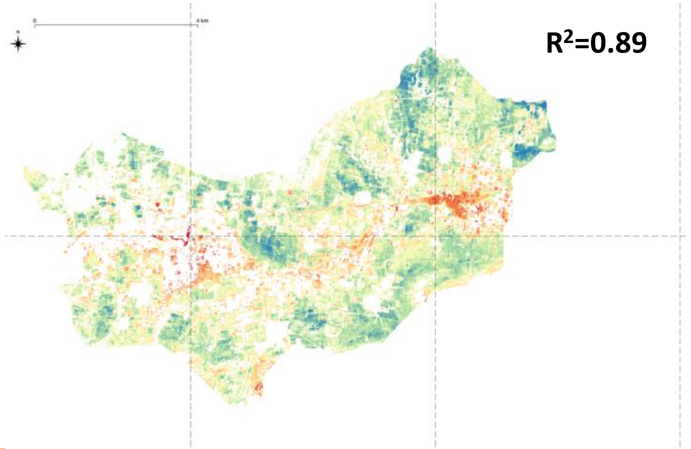
Model covariates:

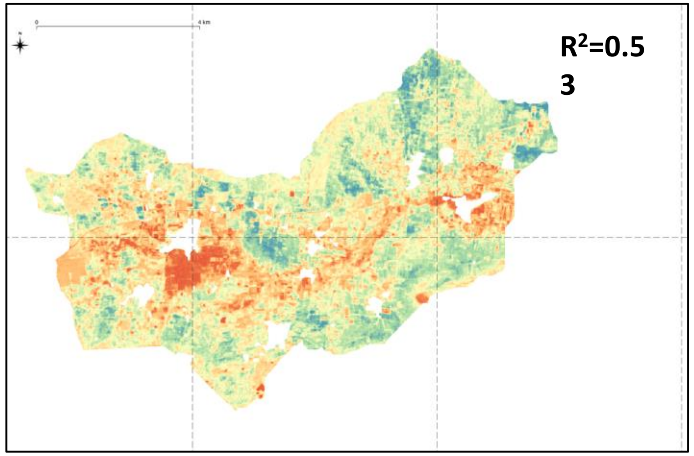
- “Classic” covariates: derivatives of DEM & NDVI.

- + all bands of Sentinel-2 imagery (10 bands)



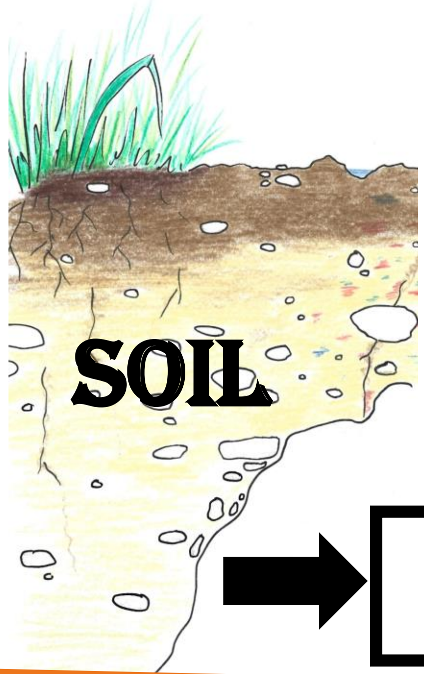




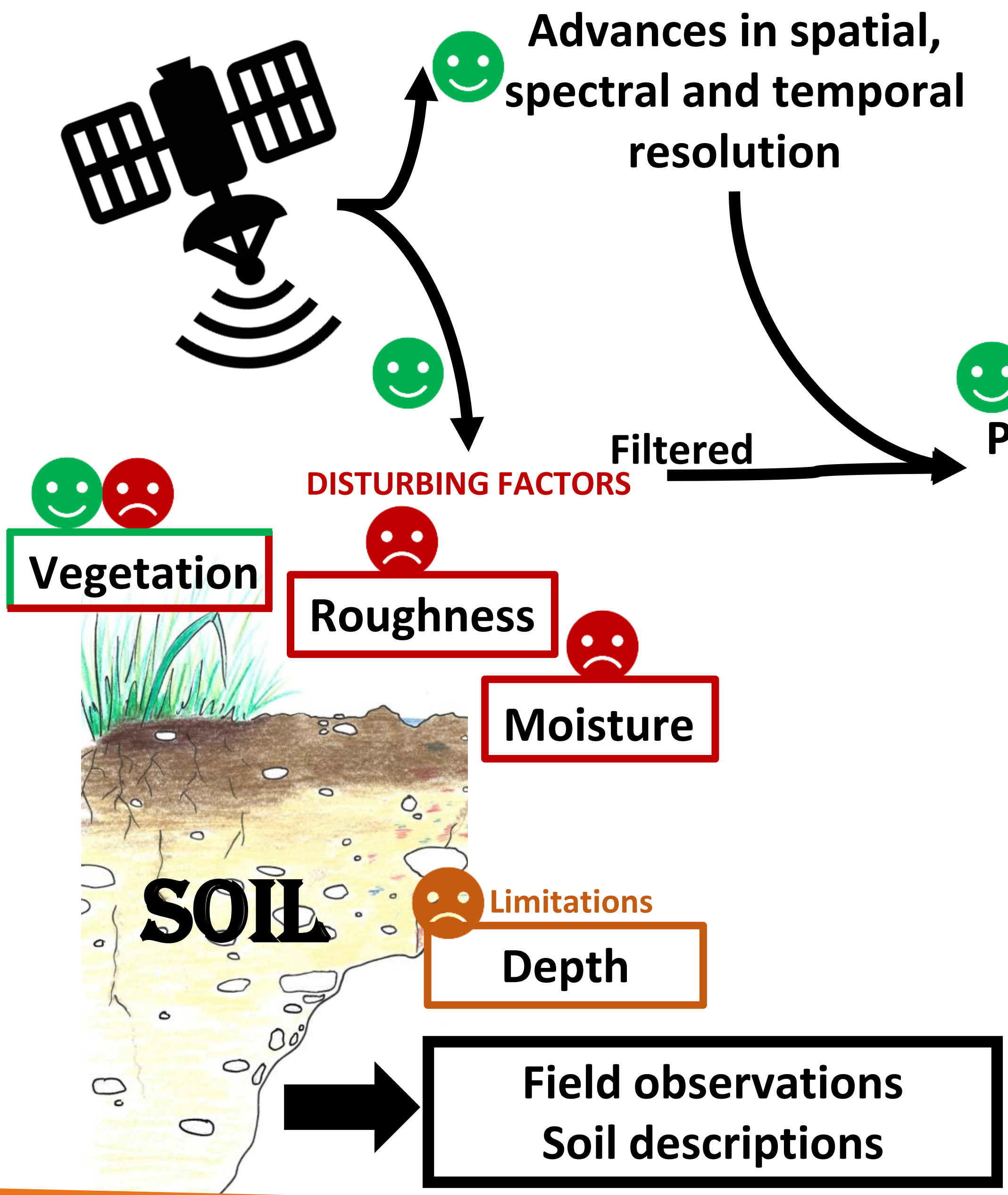


Weerasekara et al., Soumis

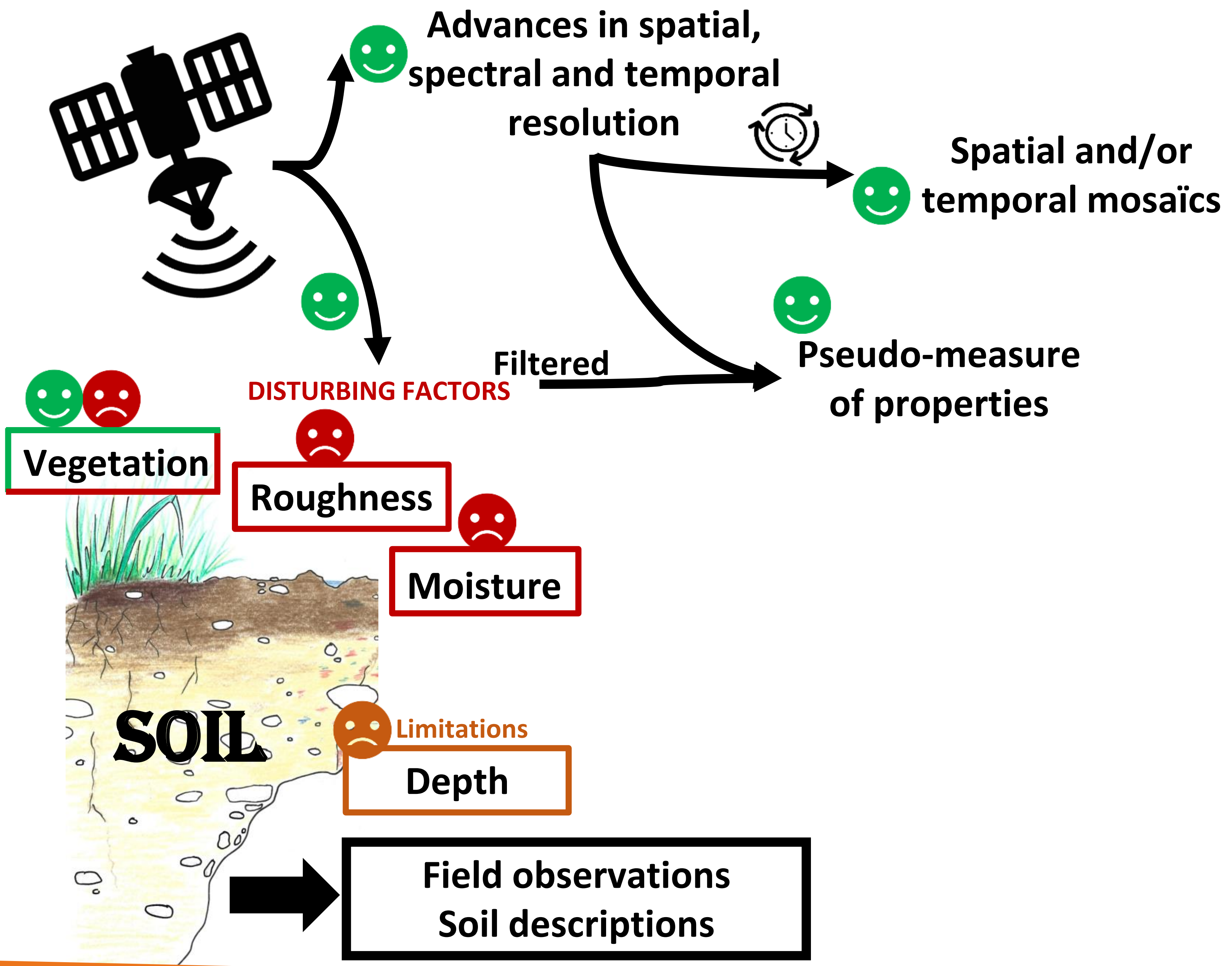
Conclusion



Field observations
Soil descriptions



Advances in spatial, spectral and temporal resolution
DISTURBING FACTORS
Filtered
Pseudo-measure of properties
Vegetation
Roughness
Moisture
SOIL
Limitations
Depth
Field observations
Soil descriptions



Advances in spatial, spectral and temporal resolution
Spatial and/or temporal mosaïcs
Filtered
Pseudo-measure of properties
DISTURBING FACTORS
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Moisture
SOIL
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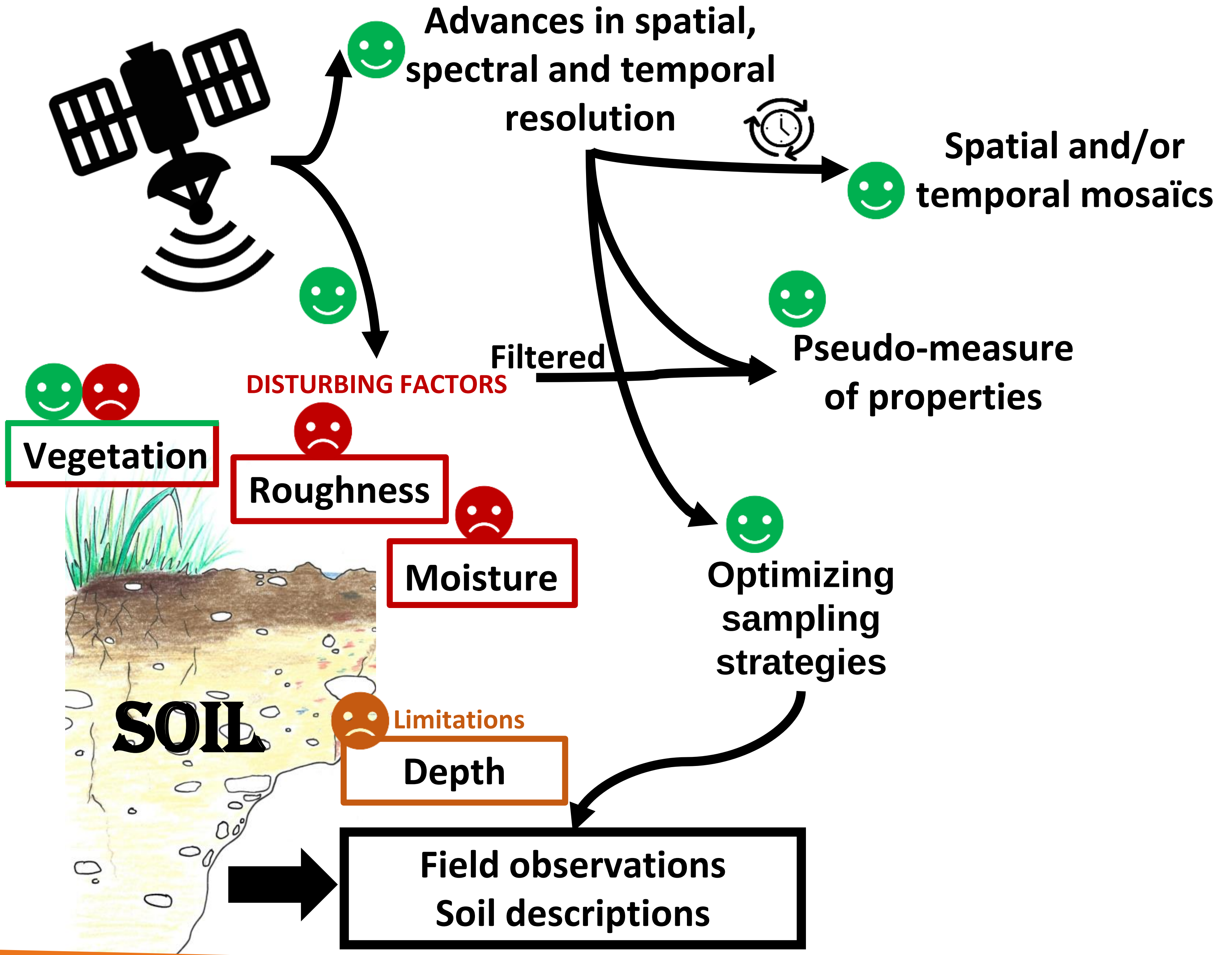
Depth
Field observations
Soil descriptions



Advances in spatial, spectral and temporal resolution
Spatial and/or temporal mosaïcs
Pseudo-measure of properties
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DISTURBING FACTORS
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Optimizing sampling strategies
SOIL
Limitations
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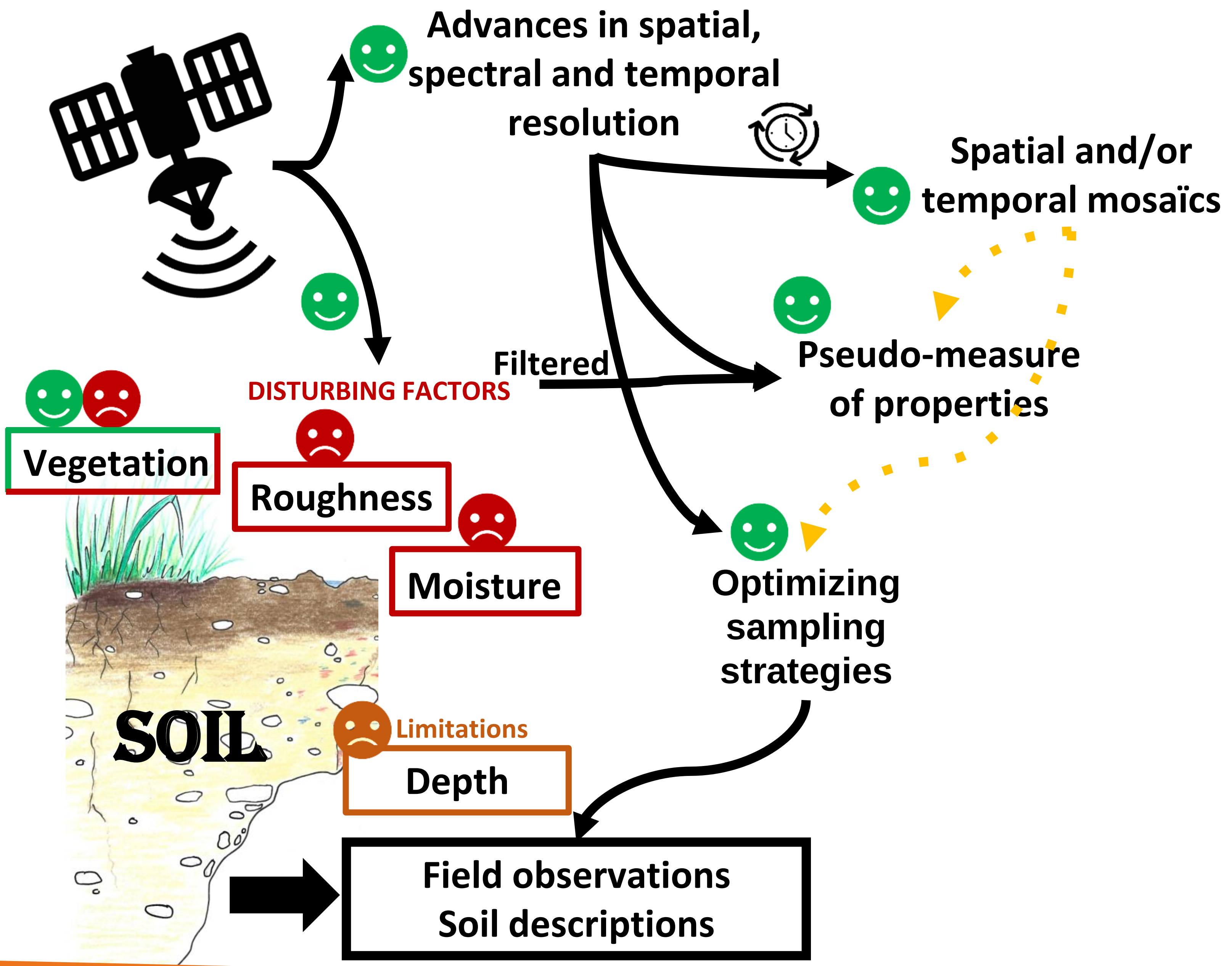
Field observations
Soil descriptions


Advances in spatial, spectral and temporal resolution
Spatial and/or temporal mosaïcs
Pseudo-measure of properties
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Optimizing sampling strategies
SOIL
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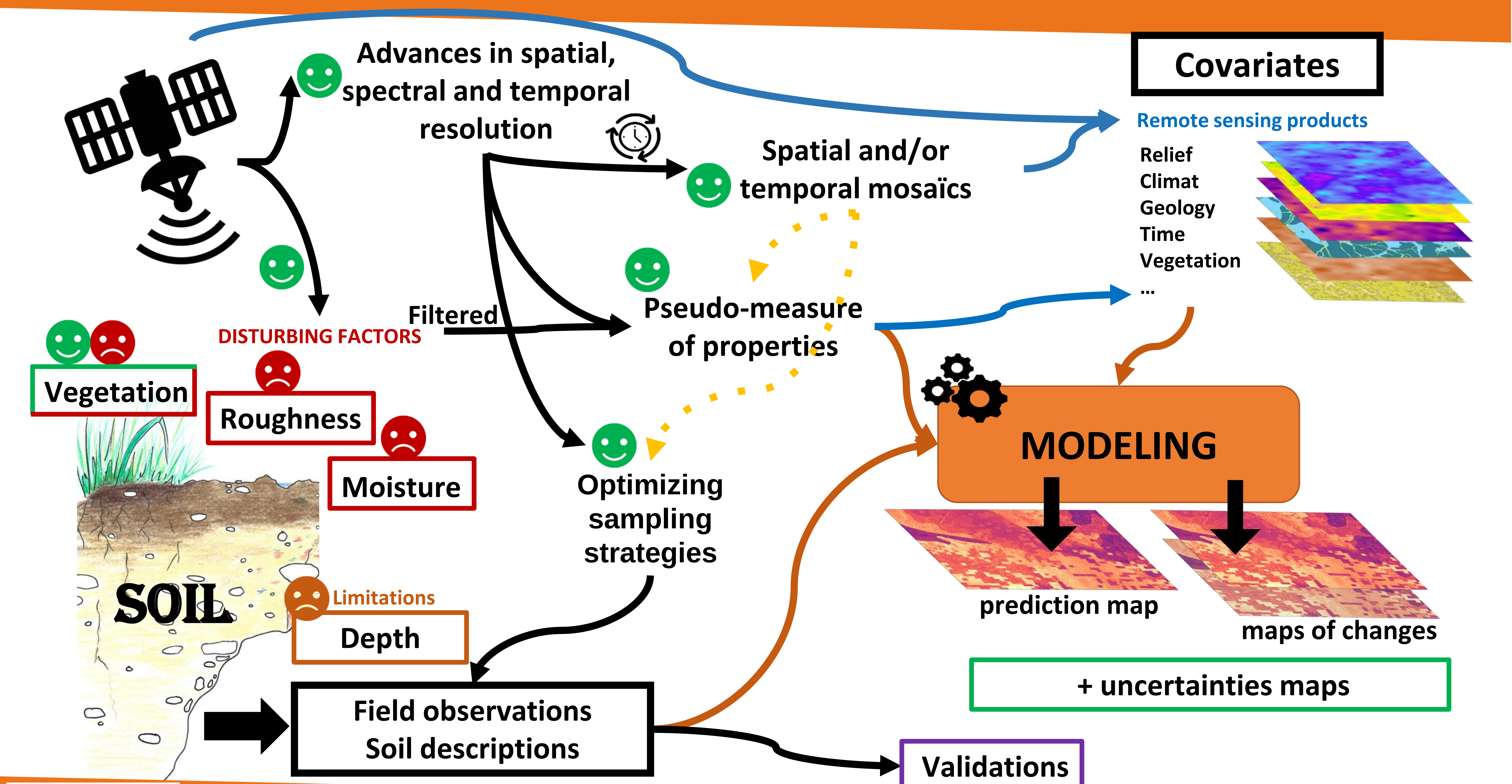
Soil descriptions


Covariates
Advances in spatial, spectral and temporal resolution
Spatial and/or temporal mosaïcs
Remote sensing products
Relief
Climat
Geology
Time
Vegetation
...
Filtered
DISTURBING FACTORS
Pseudo-measure of properties
Vegetation
Roughness
Moisture
Optimizing sampling strategies
MODELING
SOIL
Limitations
Depth
prediction map
maps of changes
+ uncertainties maps
Field observations
Soil descriptions
Validations

Thank you for your attention

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EJP SOIL
European Joint Programme

Digital Soil Mapping
The THEIA network

<u>More information:</u>

Richer-de-Forges A.C., Chen Q., Baghdadi N., Chen S., Gomez C., Jacquemoud S., Martelet G., Mulder V.L., Urbina-Salazar D., Vaudour E., Weiss M., Wigneron J.-P., Arrouays D. (2023). **Remote Sensing Data for Digital Soil Mapping in French Research - A review.** Remote Sensing. 15, 3070. Special Issue Remote Sensing for Soil Mapping and Monitoring https://doi.org/10.3390/rs15123070