# SOC3D: three dimensional soil organic carbon monitoring using VNIR reflectance spectrometry

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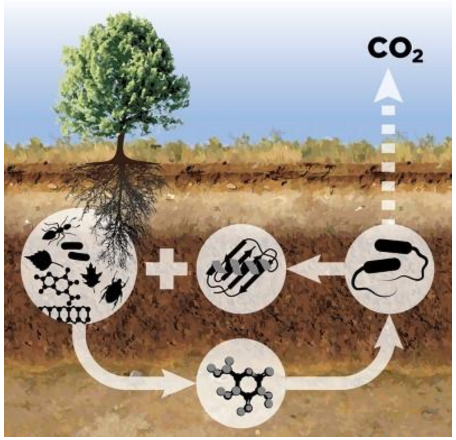
# Why Soil Organic Carbon(SOC)?

Environmental issues:

- Soil is the largest pool of terrestrial carbon.
- Land use change and management influence SOC stocks.
- Large sink of atmospheric C (due to large size and long residence time).
- Climate change.




Agricultural issues:

- Soil fertility and quality.

# Why Soil Organic Carbon(SOC)?

Some challenges:

- Large spatial variability and slow evolution of soil C over time.
- Large number of samples required prove significant changes over time.
- Sampling and analysis are too costly for treating large number of samples (Smith, 2004).

A potential solution:

- Increase the number of observations with cheaper methods of analysis

# Why Soil Organic Carbon(SOC)?

From SOC concentration (g C $kg^{-1}$ soil)

to

SOC stock (kg $m^{-2}$) = SOC (kg $kg^{-1}$) × Soil density (kg $m^{-3}$) × thickness (m)

↑

Develop cost effective tools for SOC monitoring at field and regional scales

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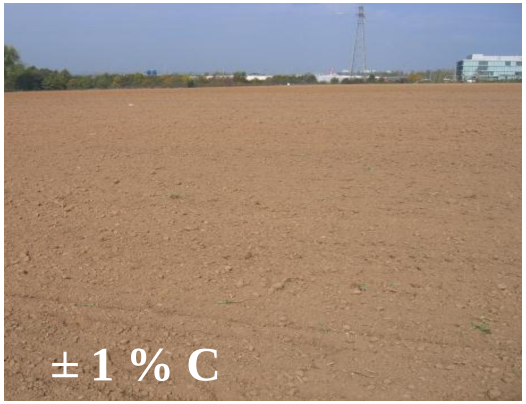
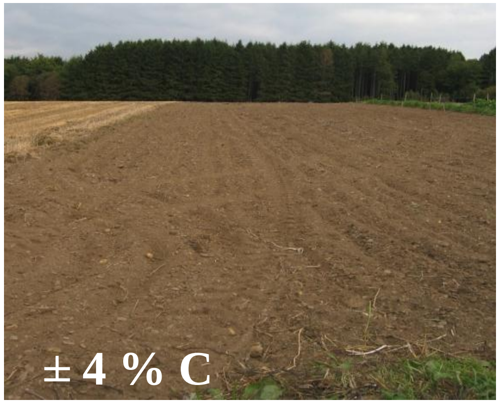
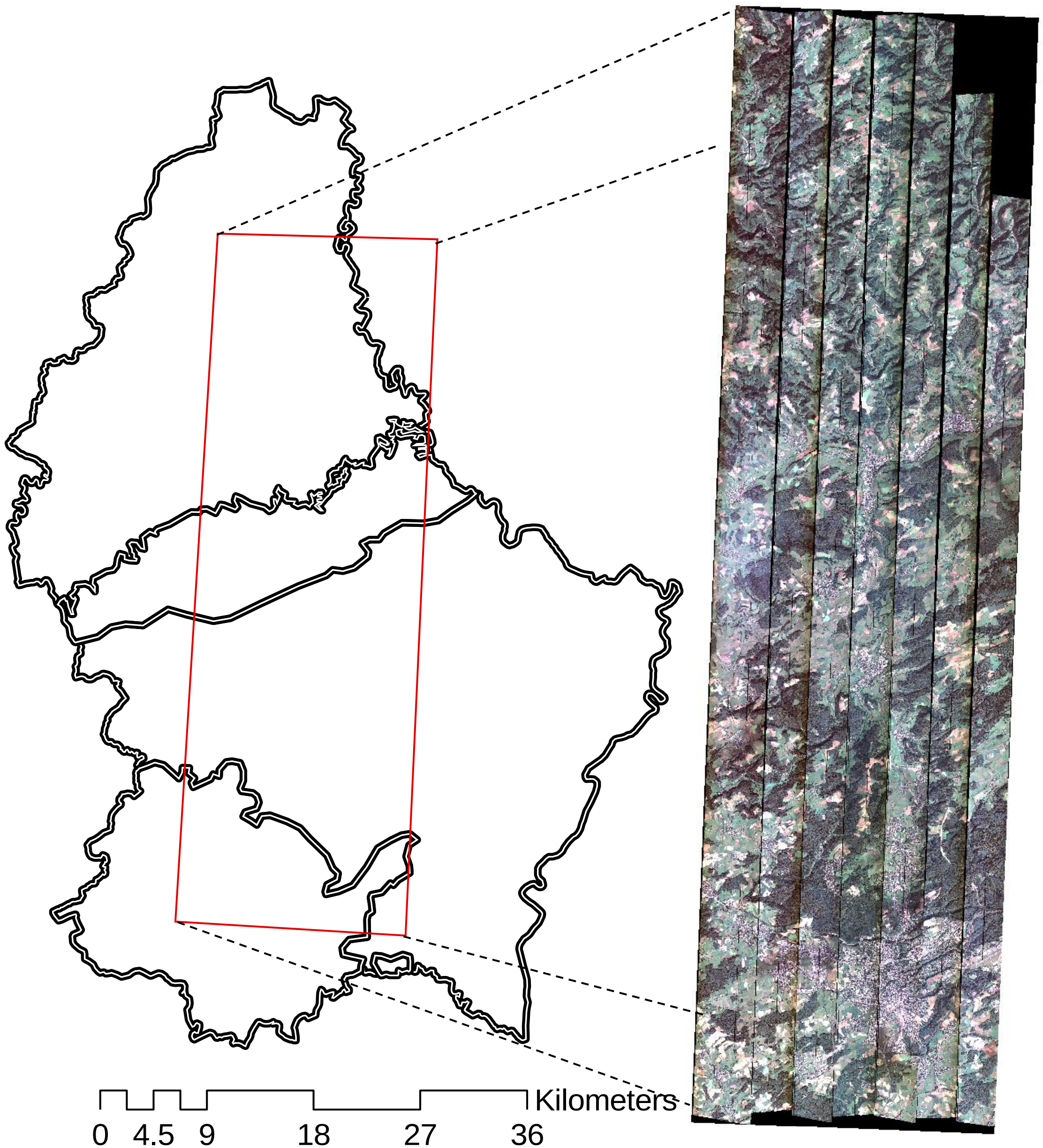


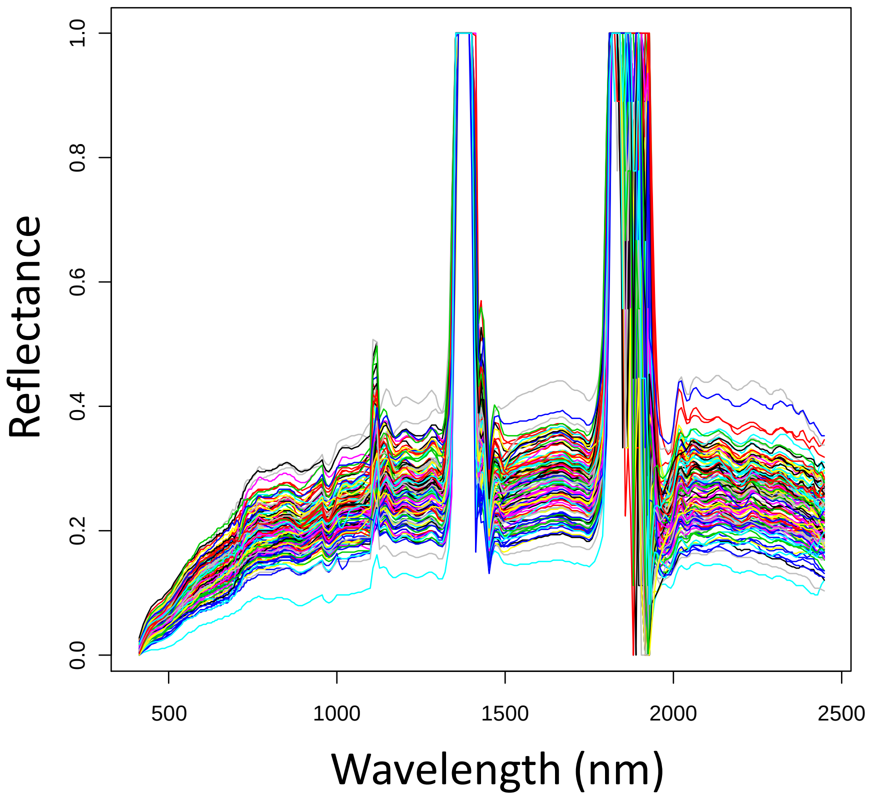
APEX sensor (Airborne Prism EXperiment)

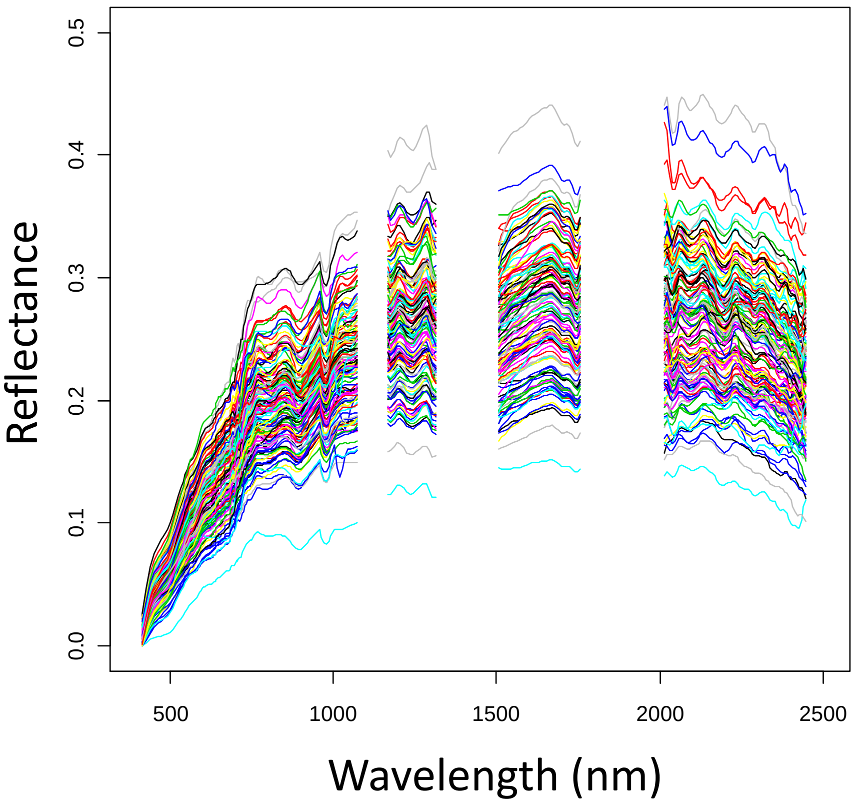
Overflight 16.09.2011, 7 flight lines, total number of 39 tiles

Hyperspectral data in 288 channels between 400 nm and 2500 nm with a 2.8 m spatial resolution

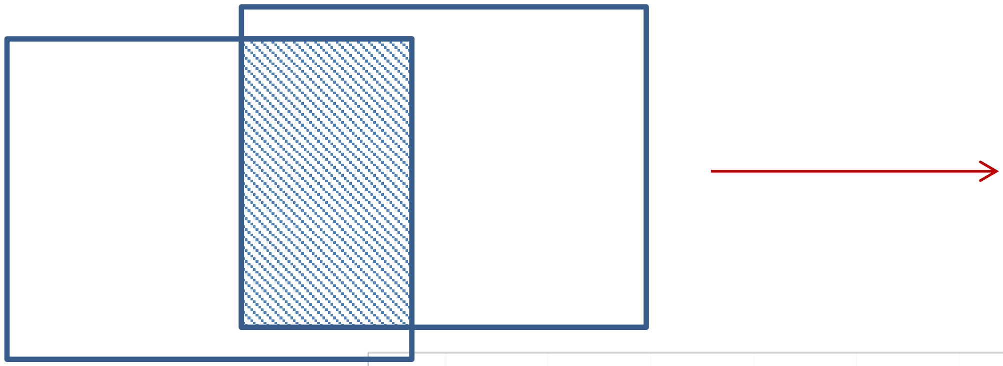


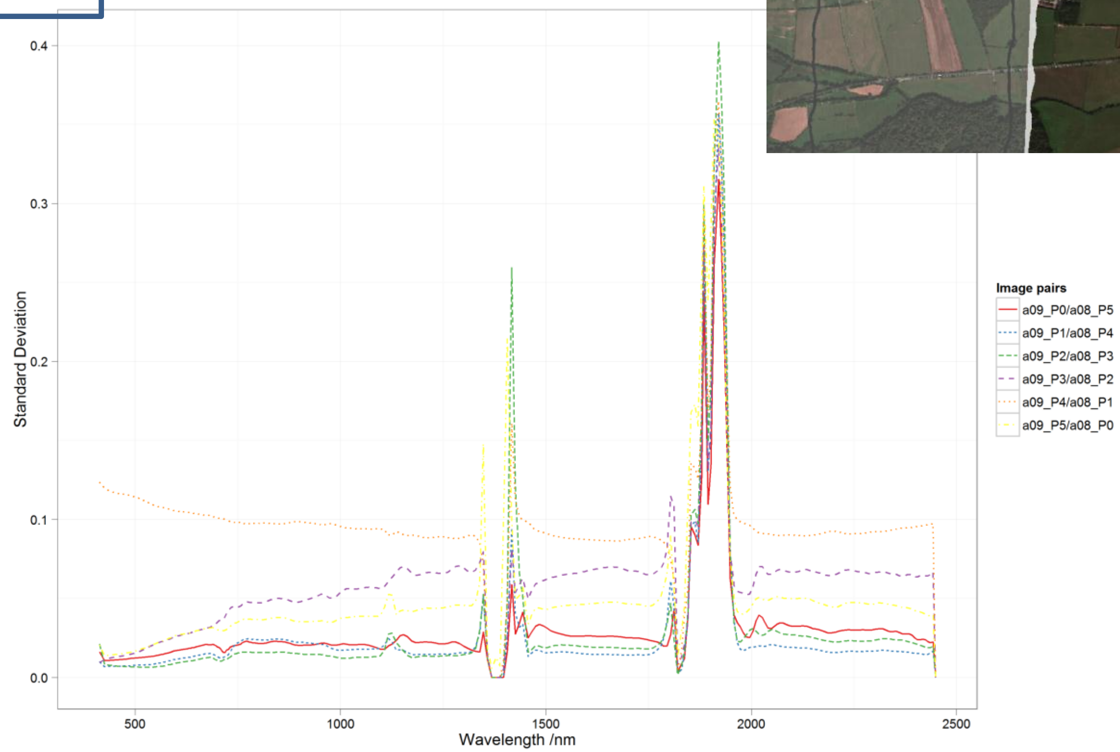
## APEX spectral data of bare soil



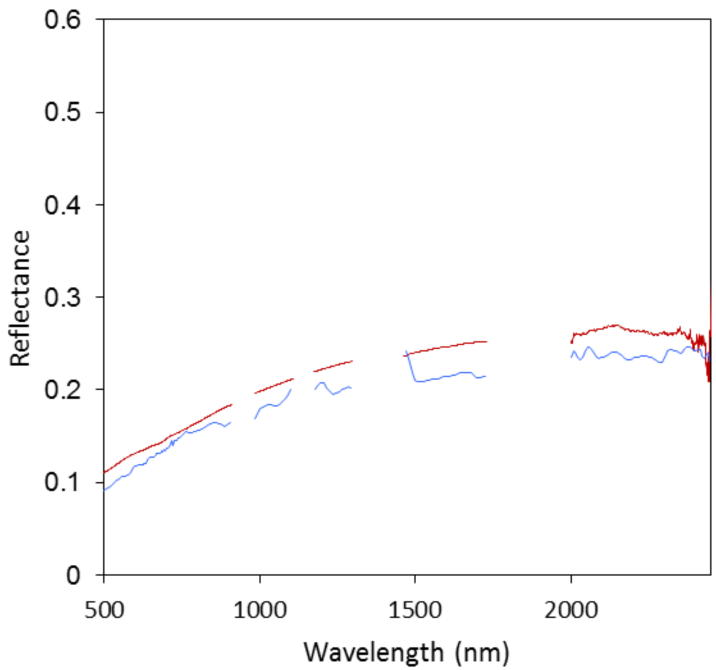



# Analysis of the spectral differences between bare fields in overlapping areas

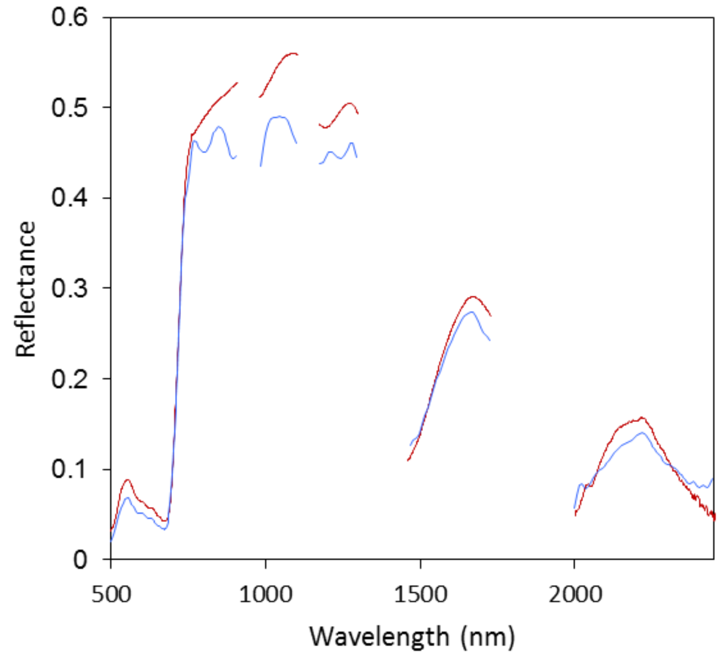




## Car park




## Grass turf



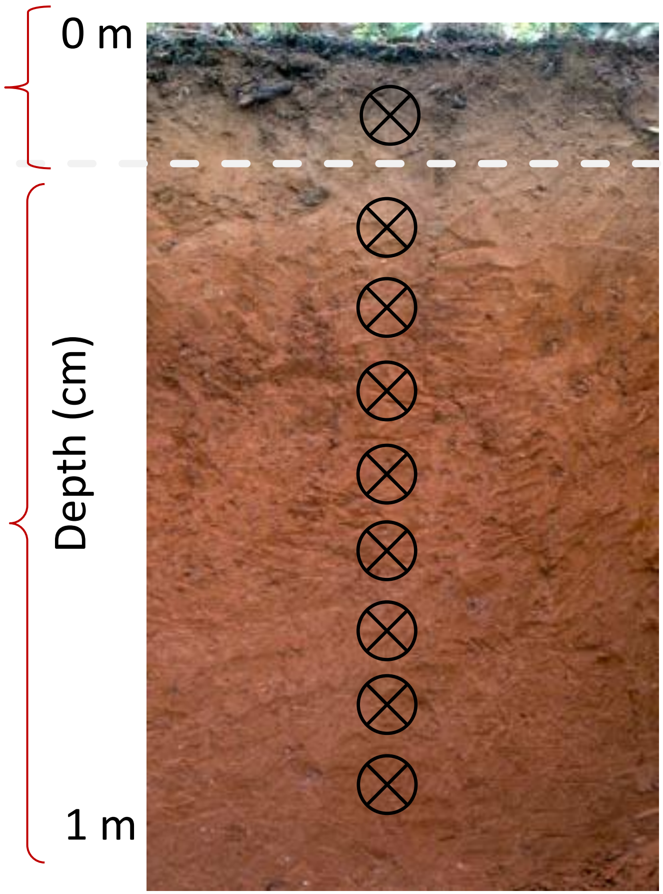

Apex data

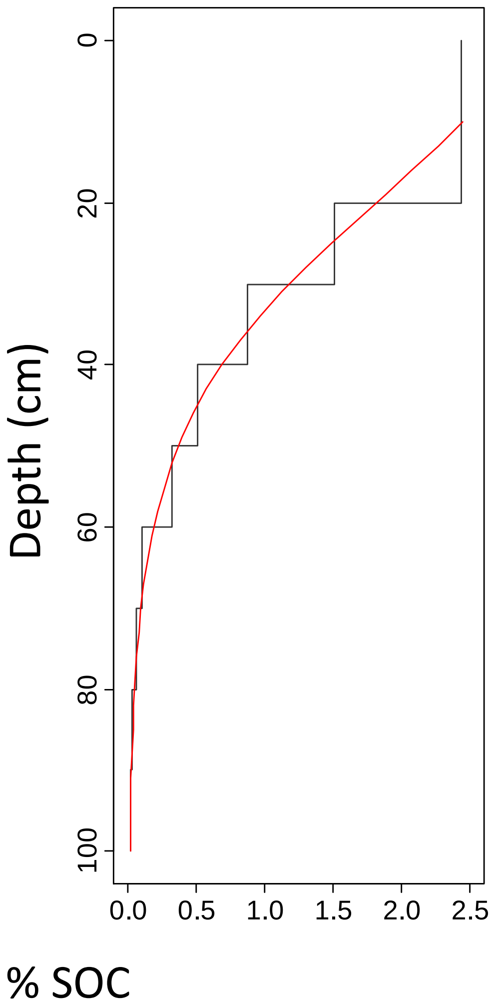
Reference

# Basic strategy

**2D** — **APEX DATA** + (Geomorphic features)

**3D** — **Geomorphic features**



VNIR imaging spectra
(APEX data)

Surface (2D ) modeling strategy

# Surface (2D) modeling strategy

VNIR imaging spectra
(APEX data)

*Delimitation of the study areas…*

Maximum likelihood classification

Identification of the bare fields

# Surface (2D) modeling strategy

Our study area comprises a total surface of ~23 $km^2$
(>1000 fields)

# Surface (2D) modeling strategy

VNIR imaging spectra
(APEX data)

↓

*Delimitation of the study areas…*

Maximum likelihood classification

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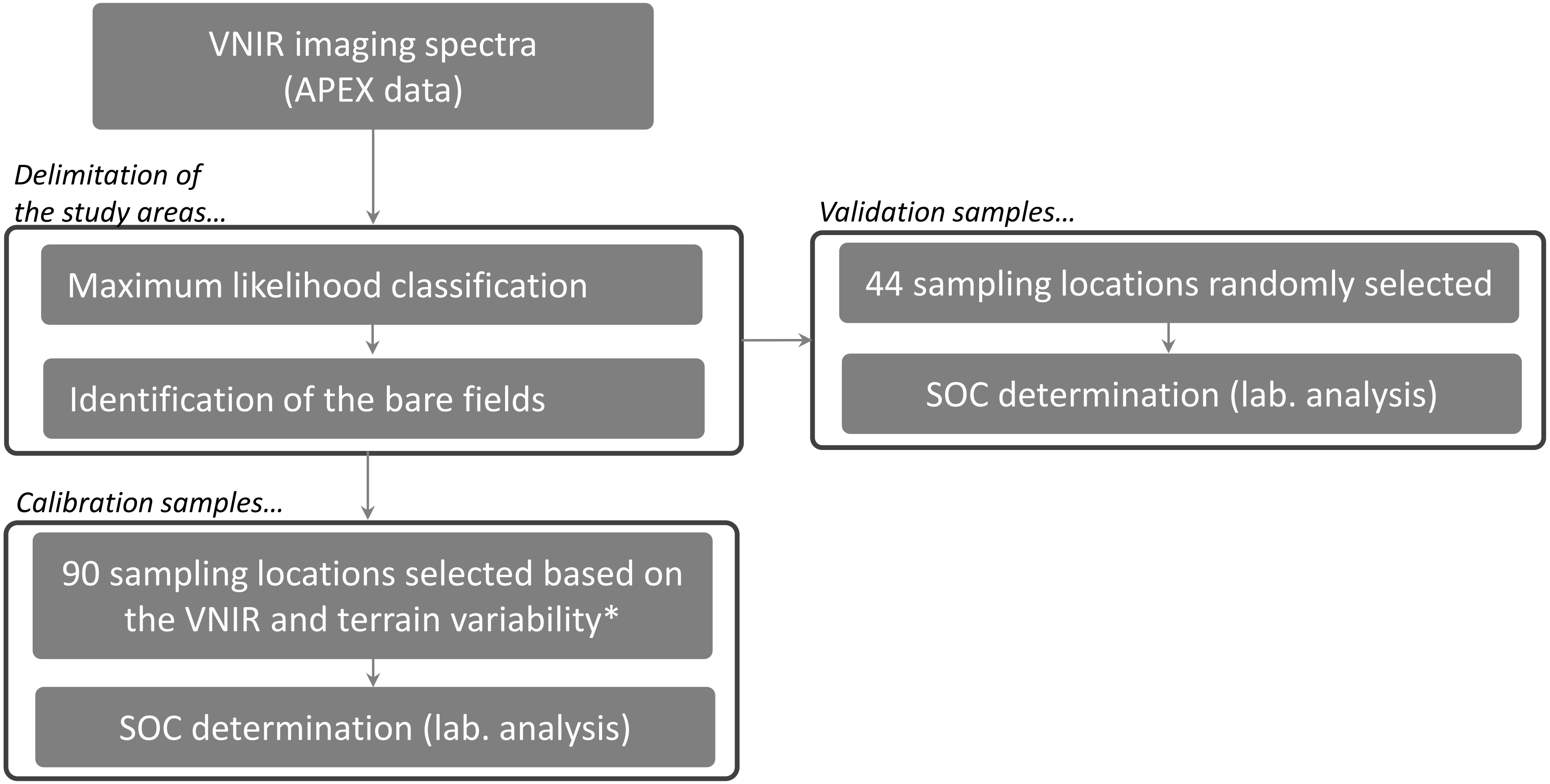
Identification of the bare fields

# Surface (2D) modeling strategy

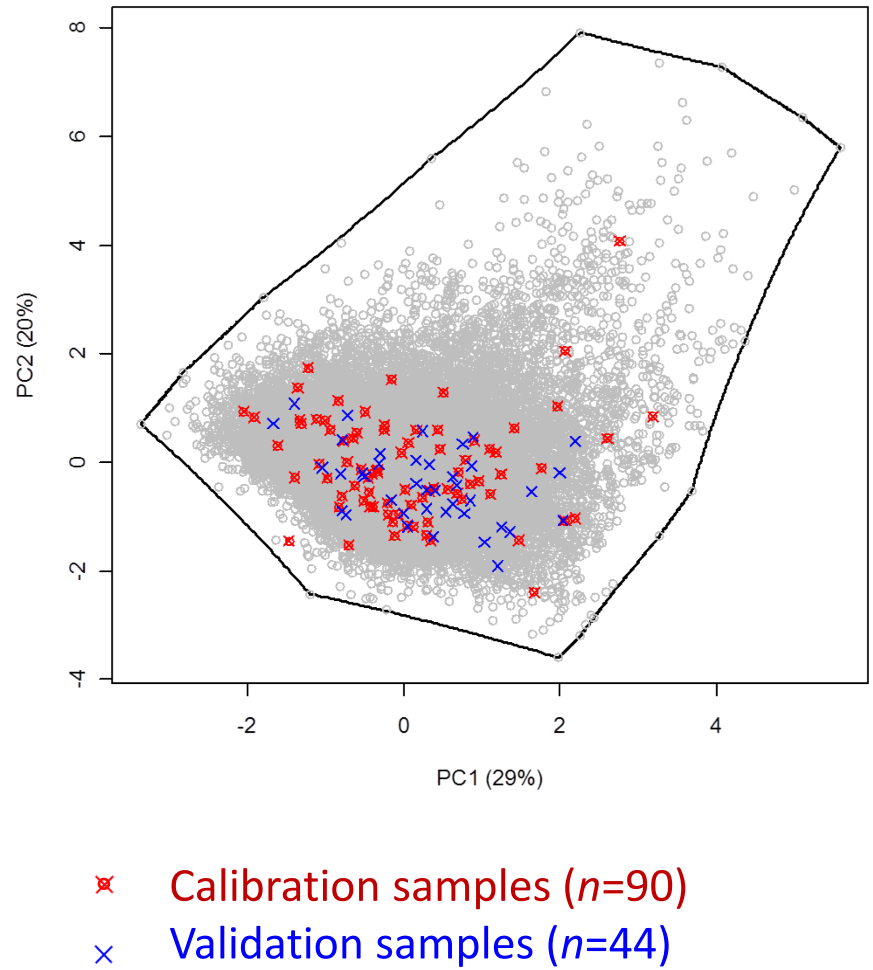



* Terrain or geomorphic features (e.g. elevation, slope, curvature, etc.) at the respective sampling locations

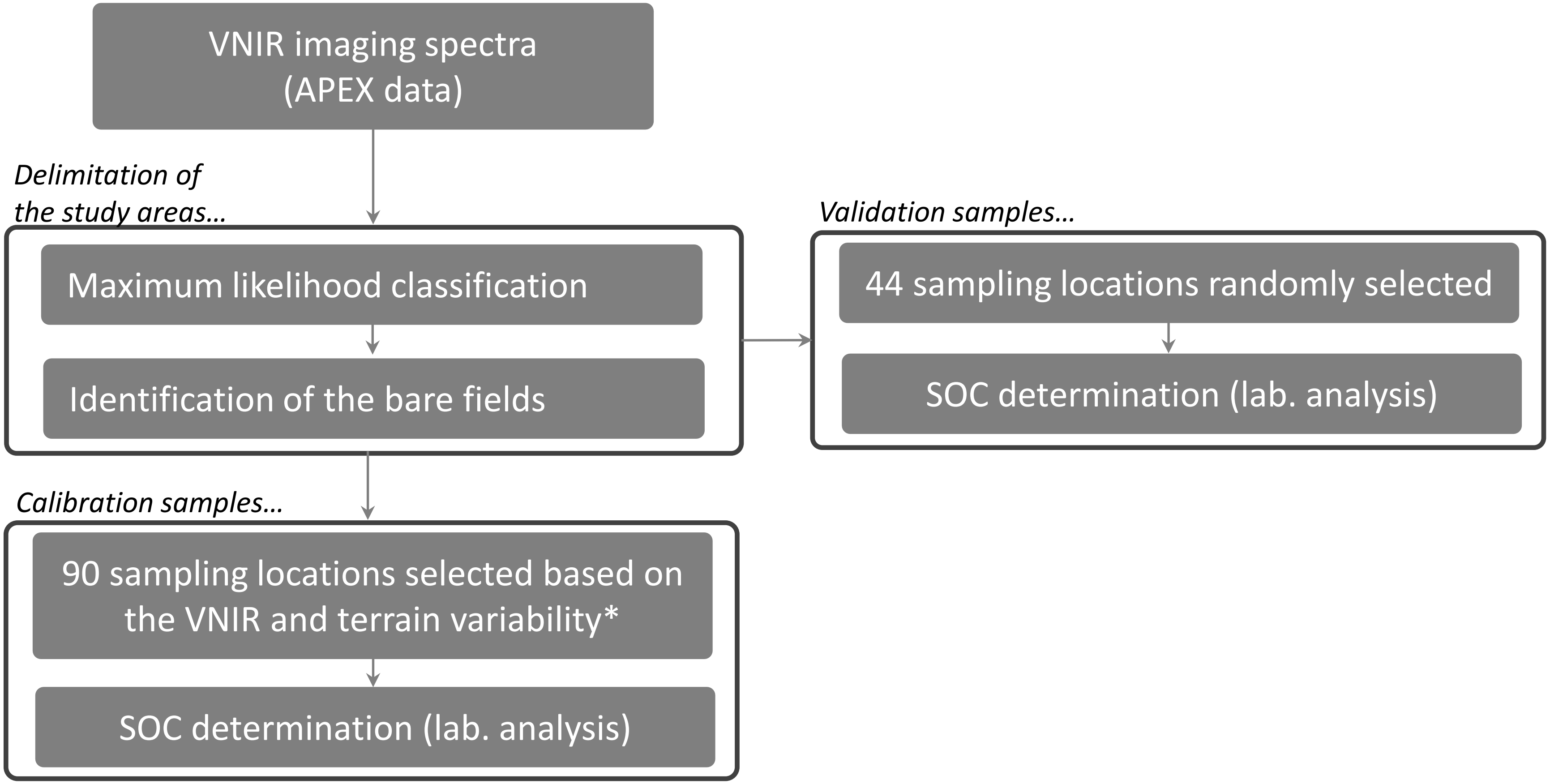
**Calibration sampling:** Select a set of samples to cover properly both the VNIR and geomorphic variability

**Validation sampling:** Select a set of independent samples to validate both the SOC models and SOC maps derived from the models

Principal component analysis
(VNIR + Terrain)




Surface (2D) modeling strategy

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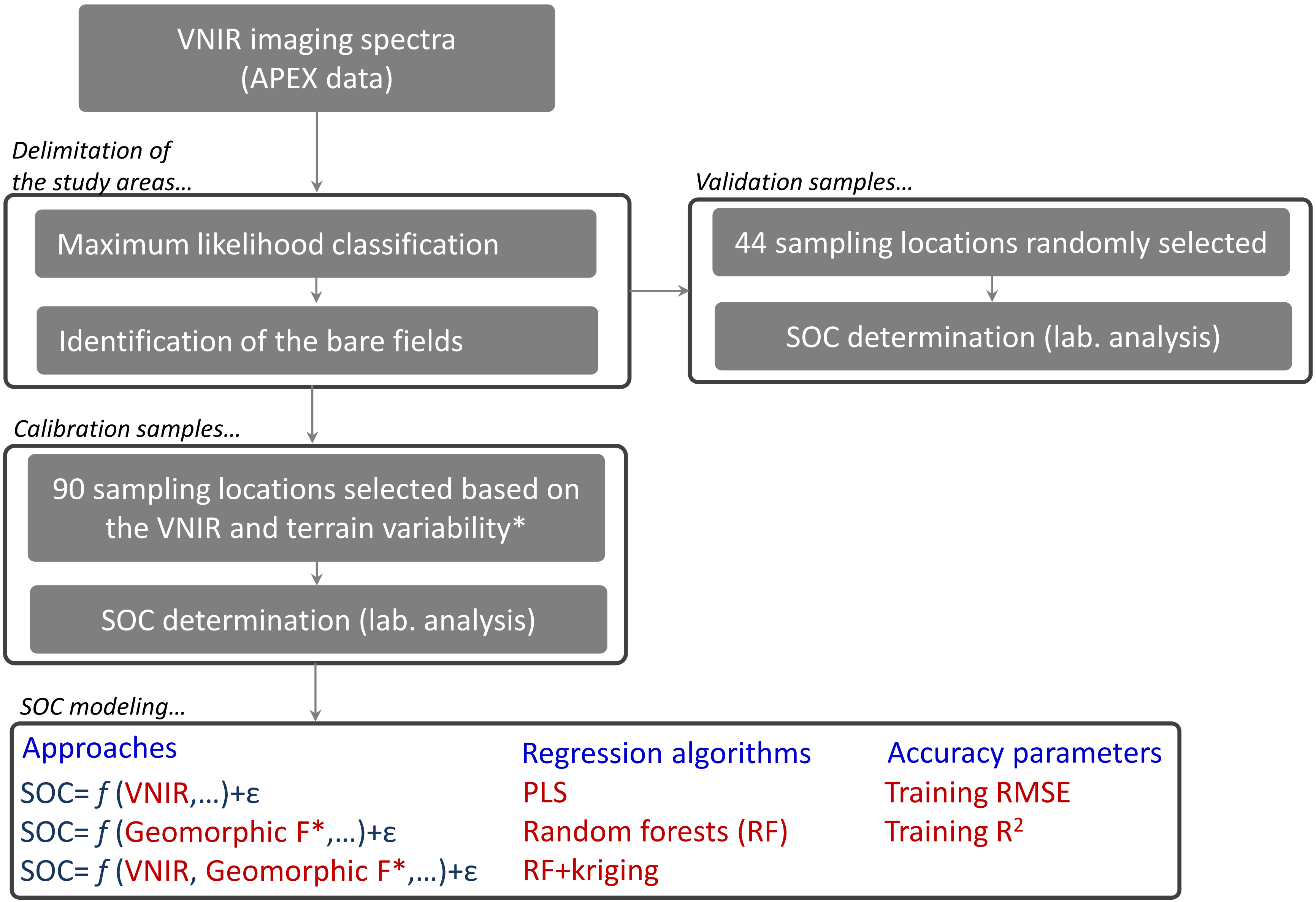


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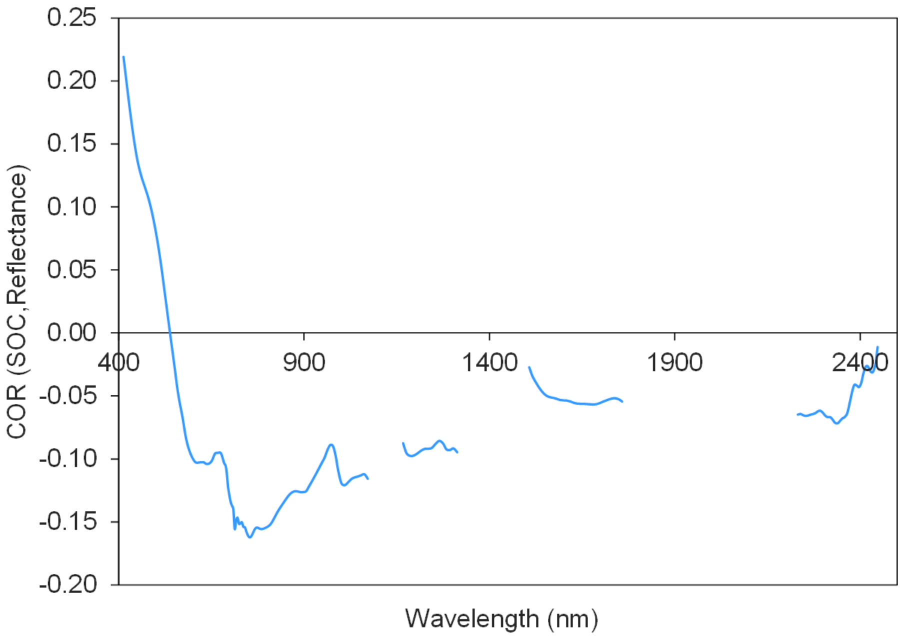
## Problem

Poor direct (univariate) correlation between each band and SOC concentration




## Proposed solution

Data mining approach to learn and exploit the multivariate relationship between SOC and VNIR features

$$SOC = f(VNIR^{*}, \dots)$$

Data mining

$$^{*}VNIR = \{R_{350nm}, \dots, R_{2500nm}\}$$

# Surface (2D) modeling strategy

VNIR imaging spectra (APEX data)

*Delimitation of the study areas…*

- Maximum likelihood classification
- Identification of the bare fields

*Validation samples…*

- 44 sampling locations randomly selected
- SOC determination (lab. analysis)

*Calibration samples…*

- 90 sampling locations selected based on the VNIR and terrain variability*
- SOC determination (lab. analysis)

*SOC modeling…*

| Approaches | Regression algorithms | Accuracy parameters |
| --- | --- | --- |
| SOC= *f* (VNIR,…)+ε | PLS | Training RMSE |
| SOC= *f* (Geomorphic F*,…)+ε | Random forests (RF) | Training $R^2$ |
| SOC= *f* (VNIR, Geomorphic F*,…)+ε | RF+kriging | |

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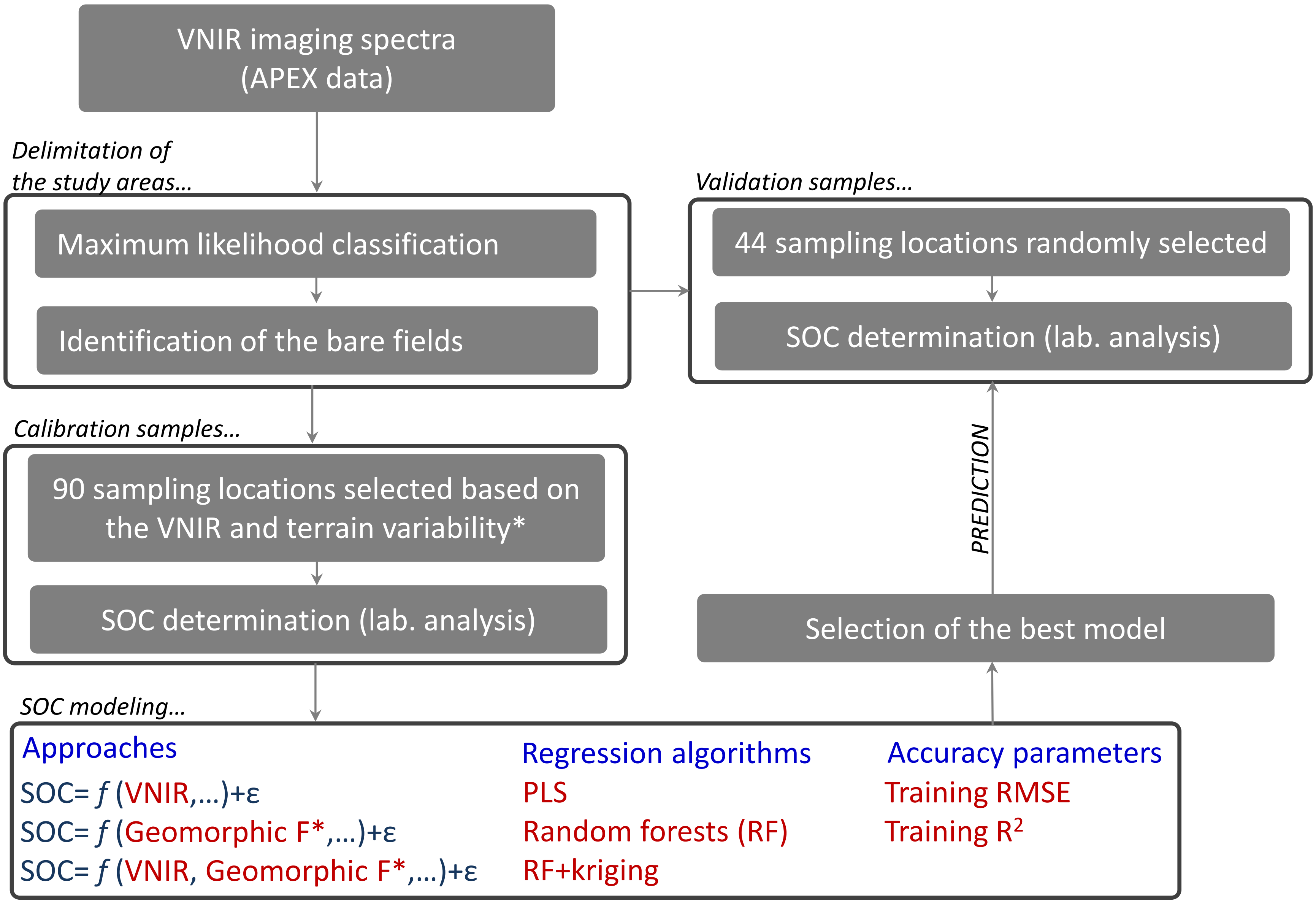
# Surface (2D) modeling strategy

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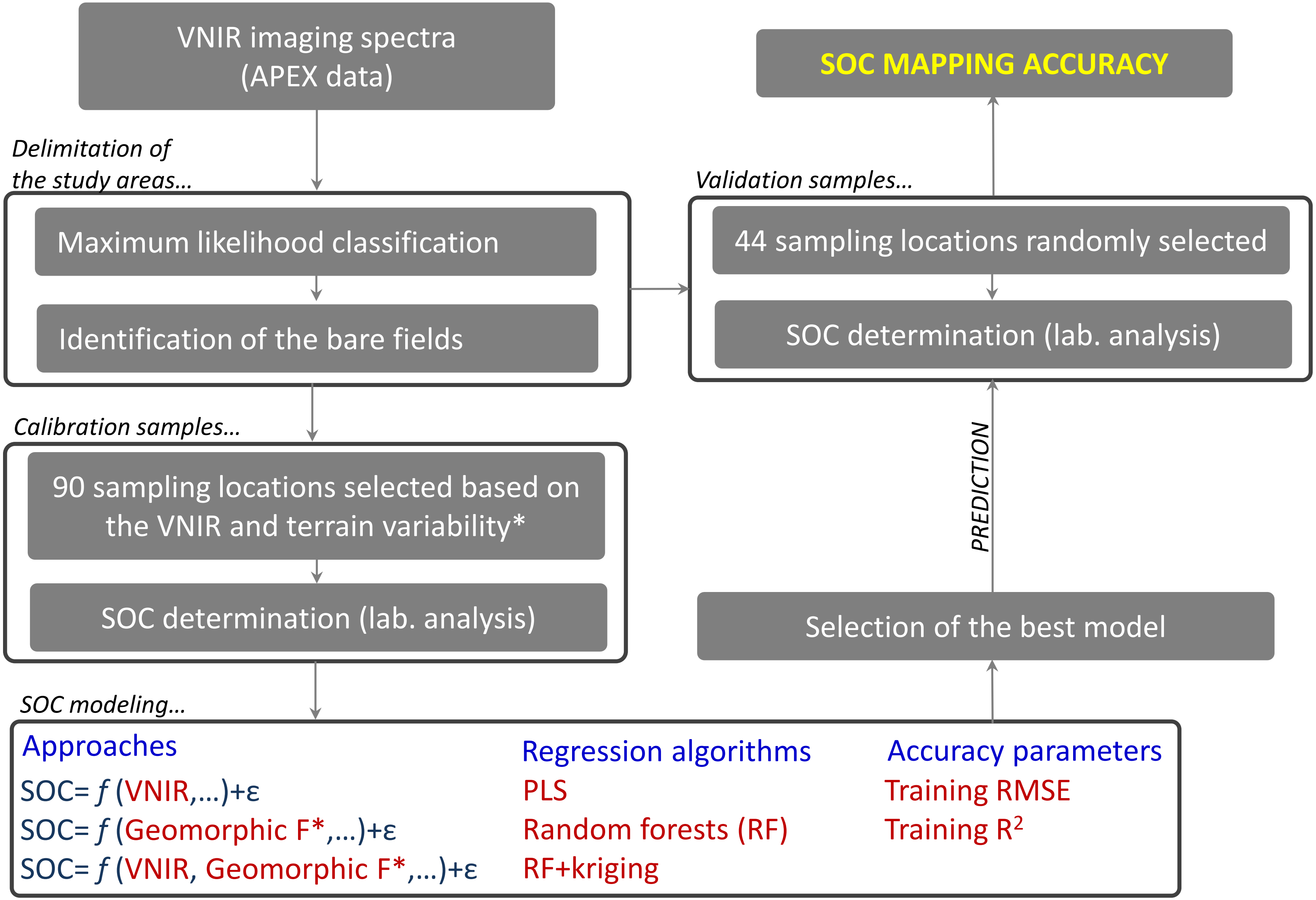


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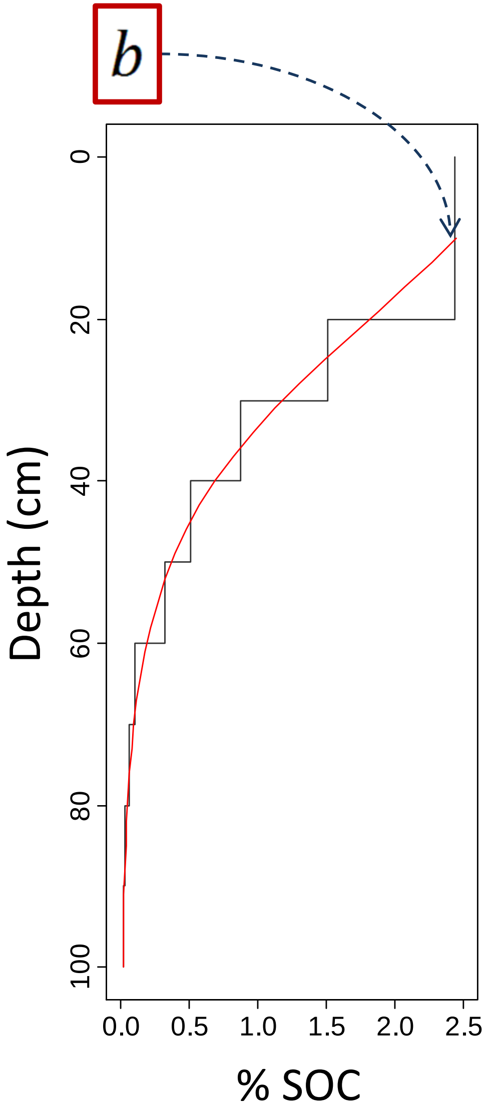
# Sub surface (3D ) modeling strategy




From discrete to continuous depth information

## Logistic SOC depth function

$$OC = b - \frac{c - b}{1 + \exp\left(a \times (depth - d)\right)}$$

*b*: SOC at the top layer

Parameter given by the SOC predicted using the VNIR data

# Sub surface (3D ) modeling strategy

$$OC = \boxed{b} - \frac{c - \boxed{b}}{1 + \exp\left(a \times (depth - d)\right)}$$

*b*: SOC at the top layer

→ Parameter given by the SOC predicted using the VNIR data

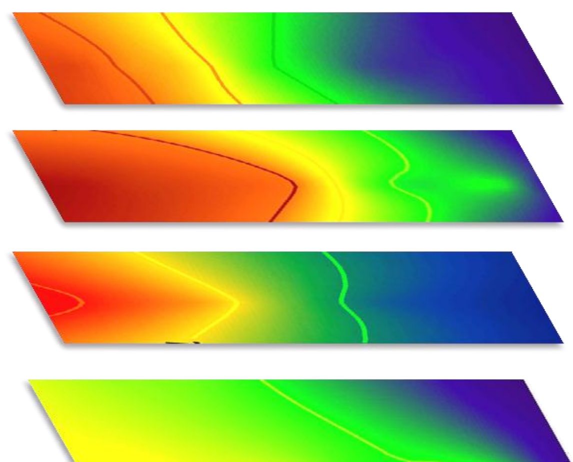
Spatial models

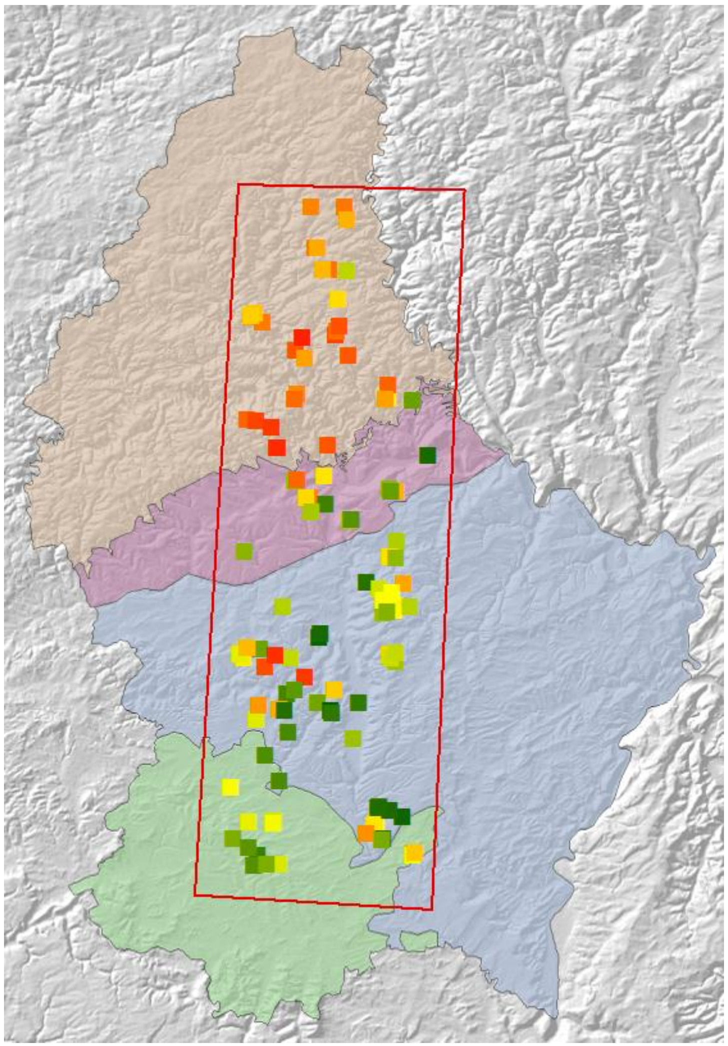
$a = f$ (Terrain attributes, ...) → a

$b = SOC_{0\text{-}10}$ → b ($SOC_{0\text{-}10}$)

$c = f$ (Terrain attributes, ...) → c

$d = f$ (Terrain attributes, ...) → d





*Agro-pedological regions*

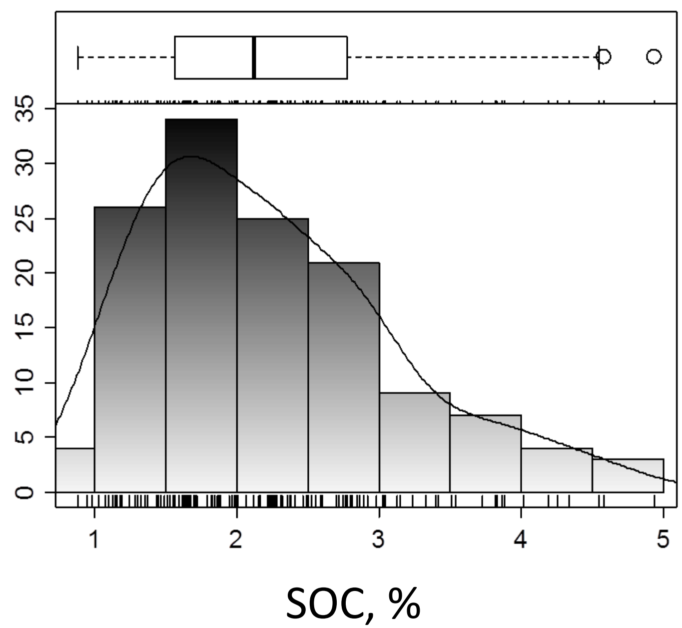
- Oesling area
- Redange-Diekirch area
- Central area
- Minette area

SOC, %

4.58

0.88

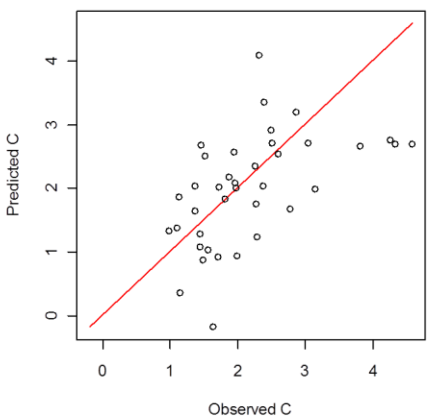
## Surface (2D) SOC mapping



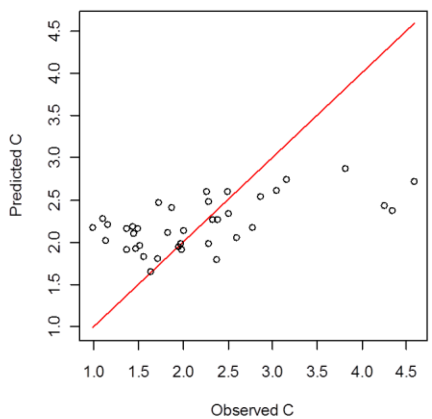
| Features | Algorithm | Training | | Validation | |
|---|---|---|---|---|---|
| | | R2 | RMSE | R2 | RMSE |
| Spectra | PLS | 0.48 | 0.64 | 0.28 | 0.88 |
| Terrain | RF | 0.37 | 0.69 | 0.21 | 0.81 |
| Terrain+Spectra | RF | 0.54 | 0.55 | 0.63 | 0.64 |
| Terrain+Spectra | RF+Kriging | 0.54 | 0.54 | 0.72 | 0.57 |

## Validation plots

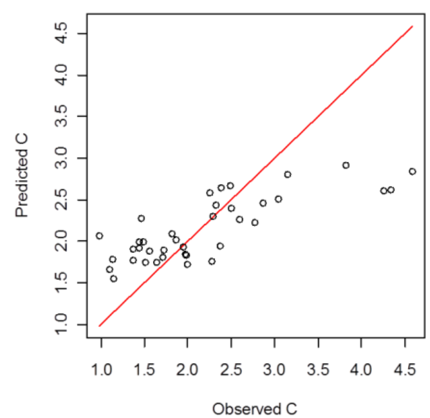
Spectra
PLS



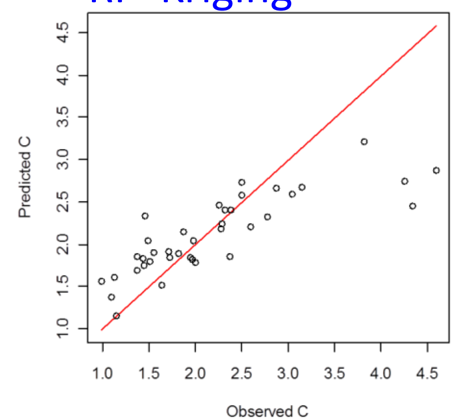

Terrain
RF




Terrain+Spectra
RF

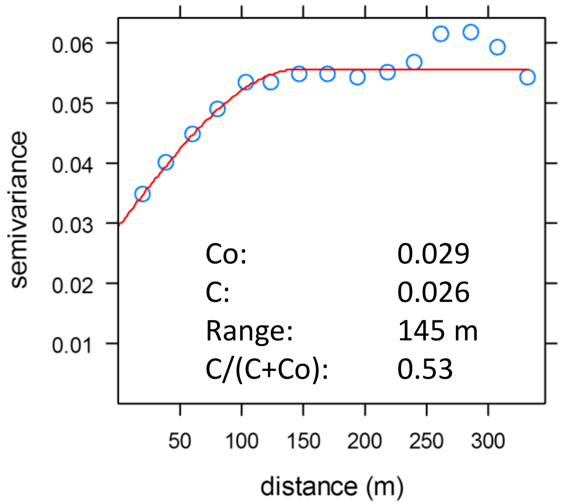


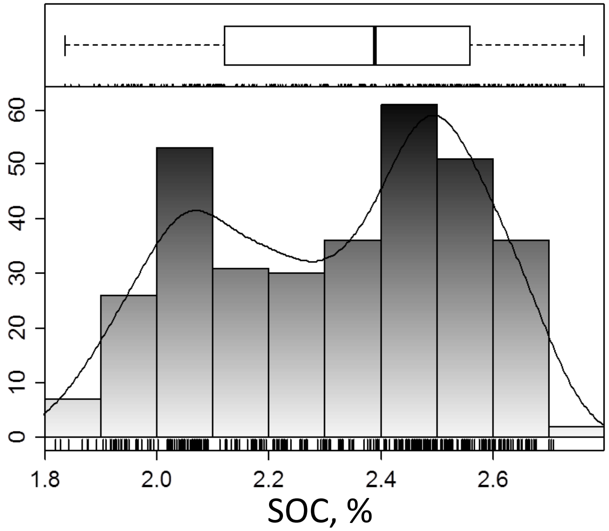

Terrain+Spectra
RF+Kriging

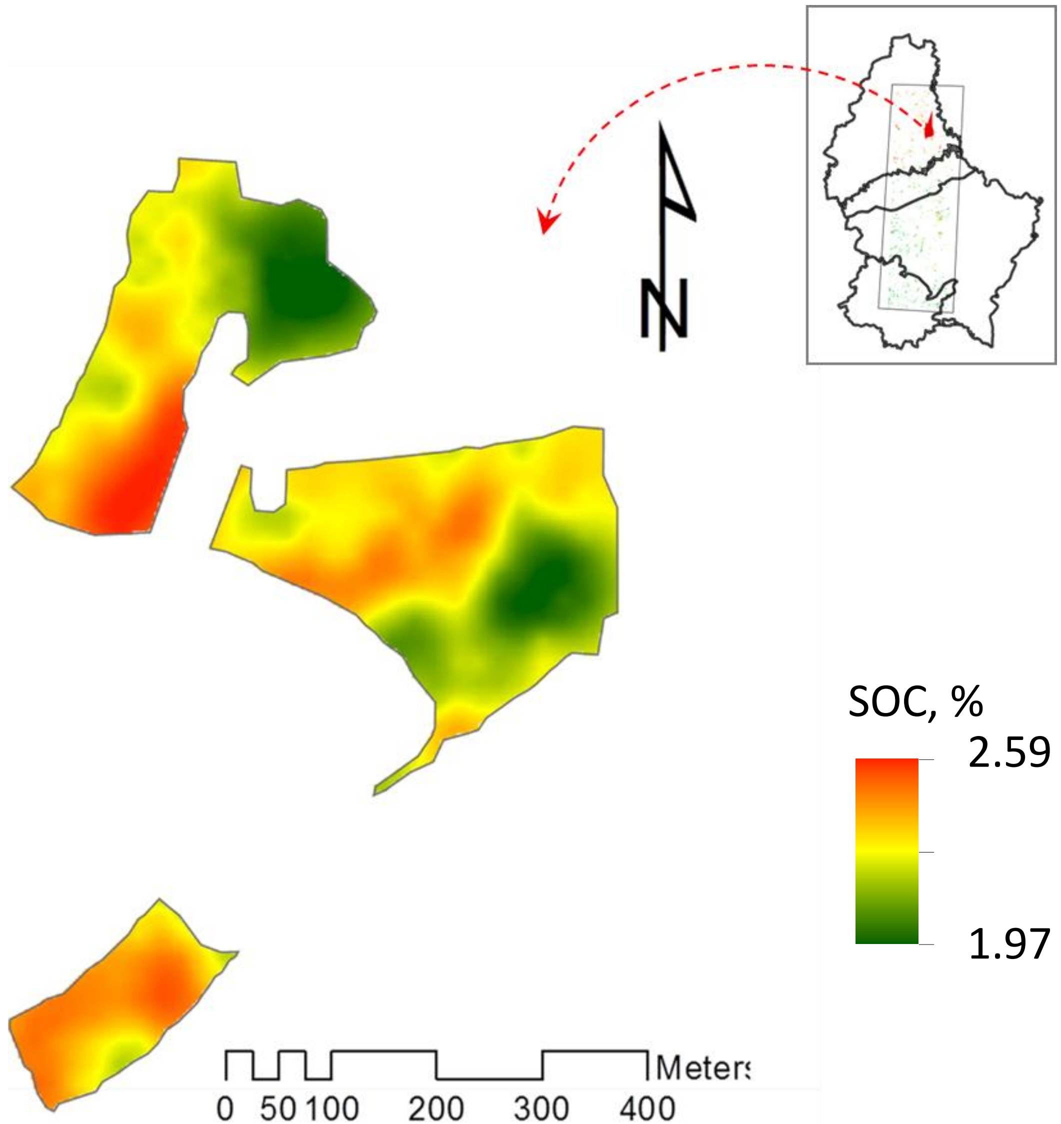


# Spatial prediction of SOC using Random Forests – kriging

Example:



- The selection of the sampling locations (for models calibration) should ensure a good coverage of the VNIR and geomorphic variability in order go obtain reliable models of SOC.

- The strategy for the selection of the sampling locations is crucial specially when the number of observations is limited.

- The integration of imaging spectrometry and geomorphometry in combination with a sophisticated spatial data mining technique considerably improve the spatial prediction of SOC content.

- We consider that the prediction performance of the models could be improved by increasing the number of observations.

- The improvement on the APEX data correction could improve the prediction performance of the VNIR models

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# Thank you for your attention

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