SOC3D: three dimensional soil organic carbon mapping using VNIR reflectance spectrometry

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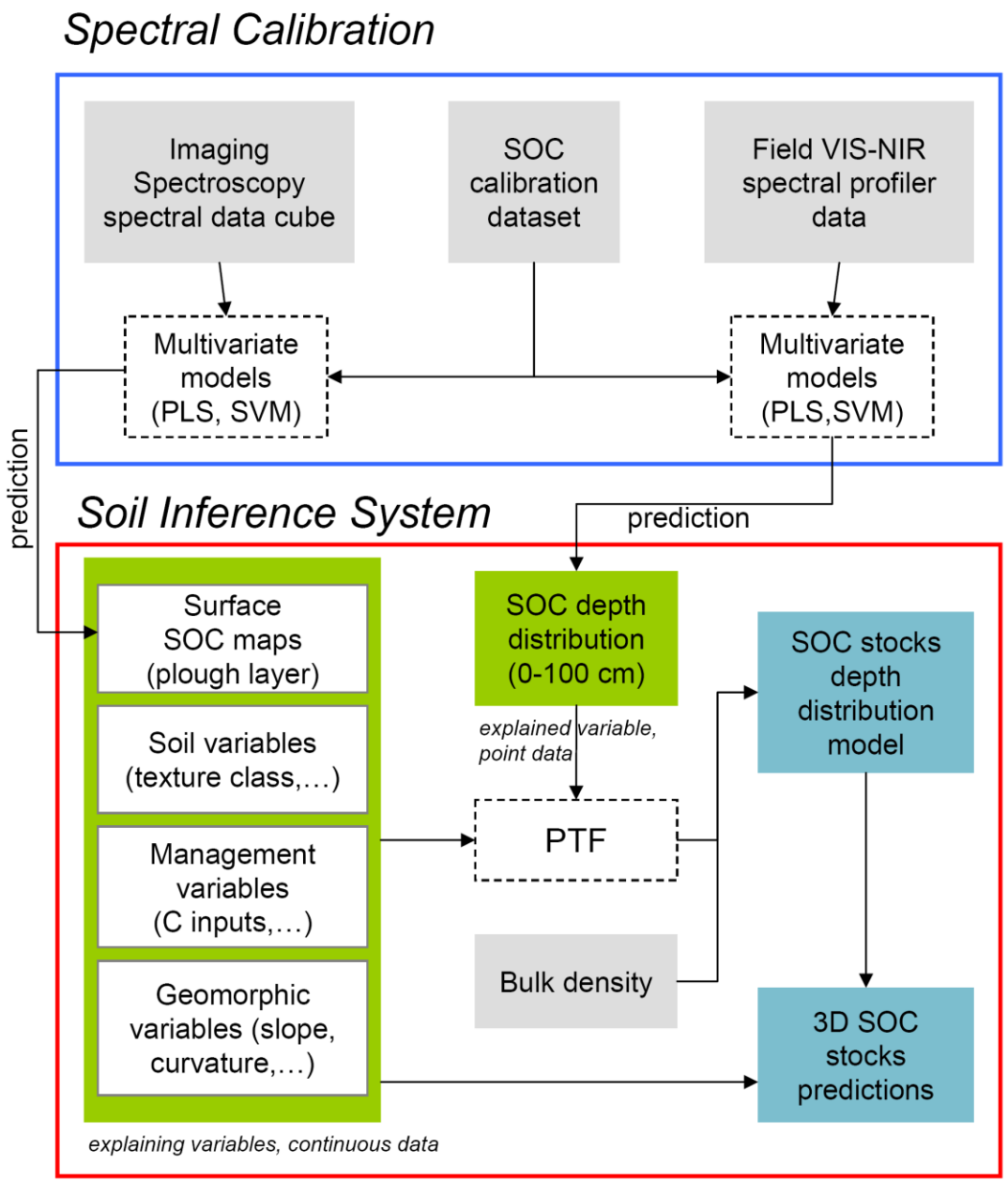
Objective

Develop a methodology to represent the variation in SOC of croplands including its vertical distribution

Proposed Methodology



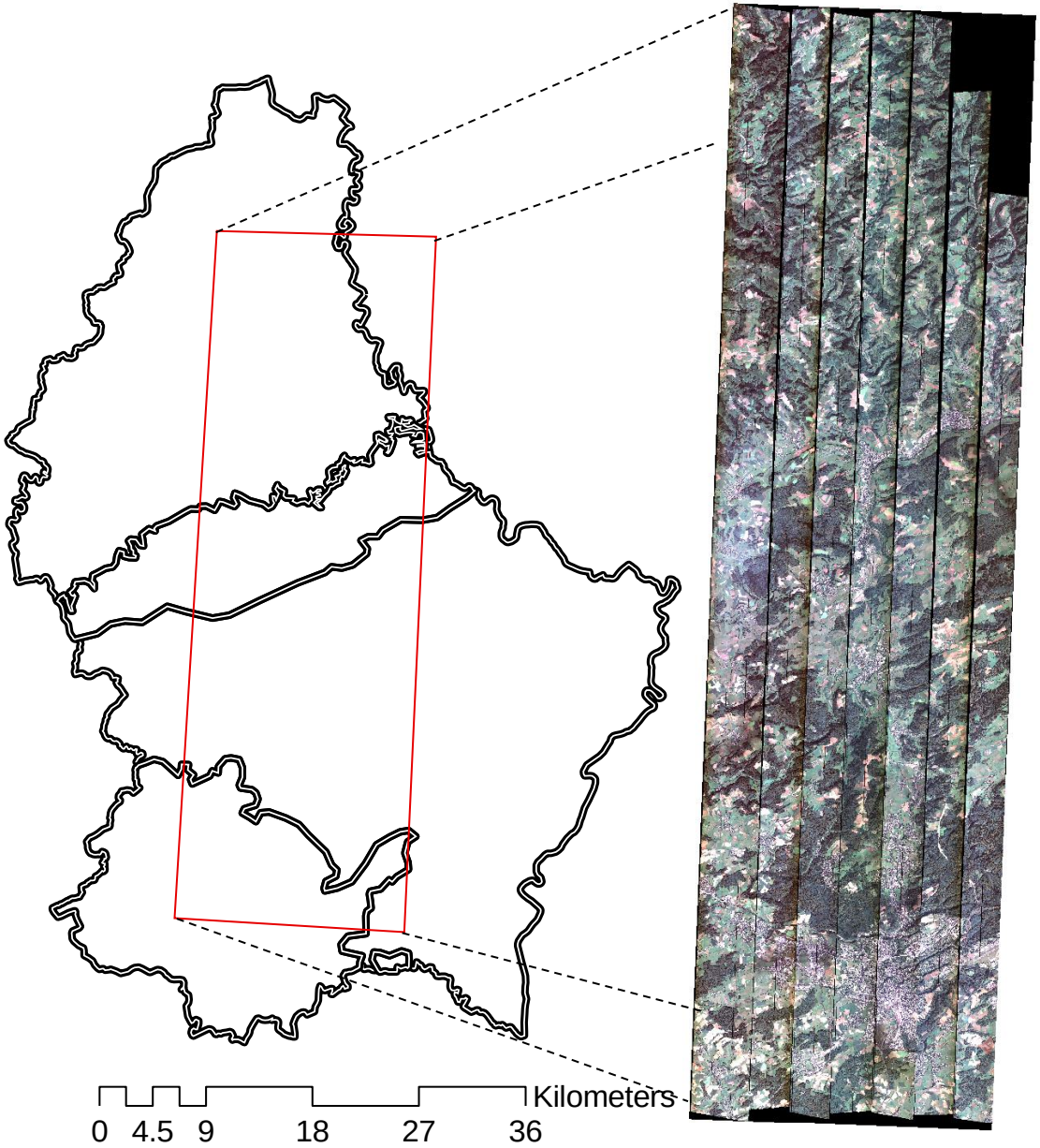
APEX sensor (Airborne Prism EXperiment)

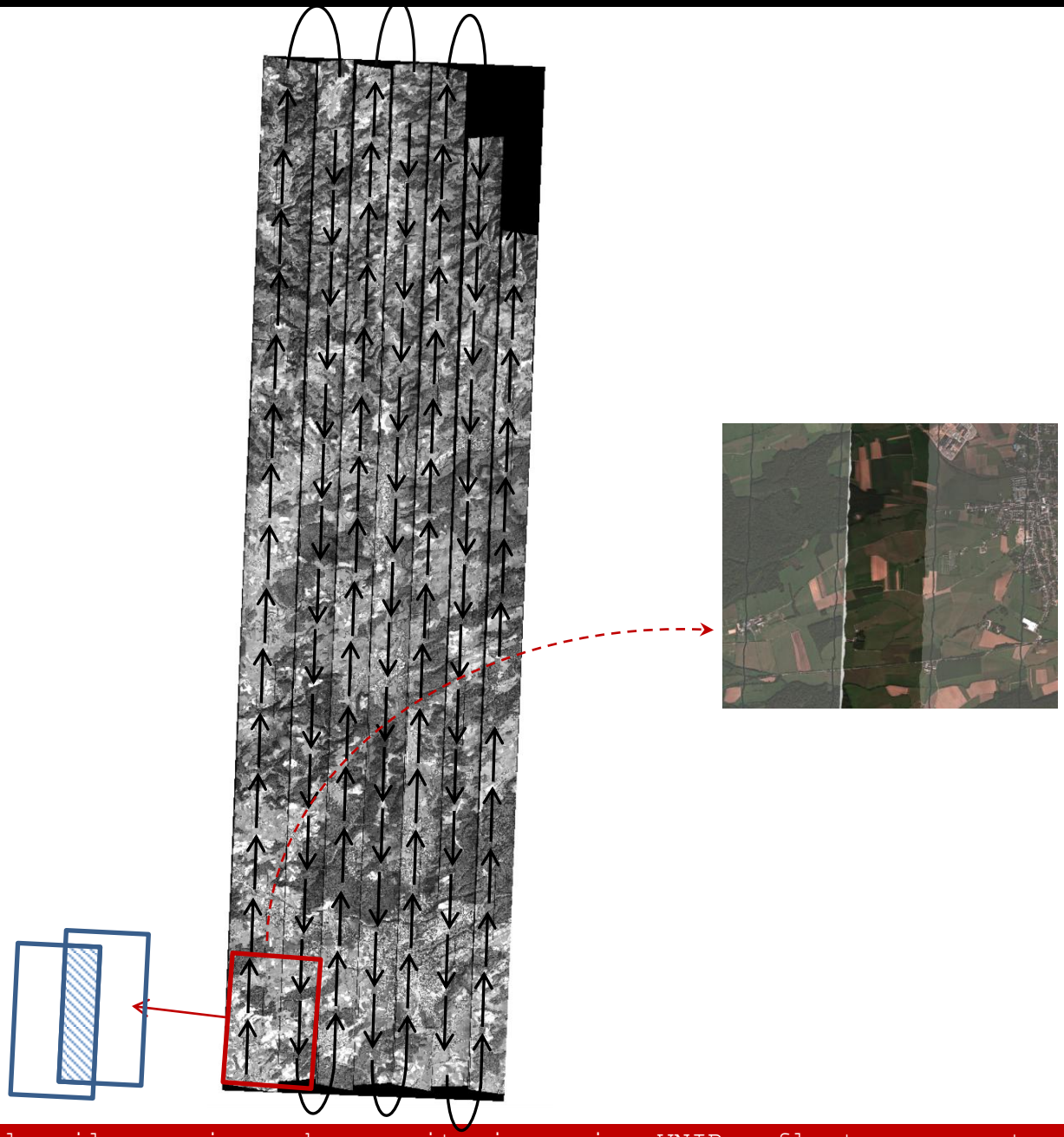
Hyperspectral data in 288 channels with a 2.8 m spatial resolution

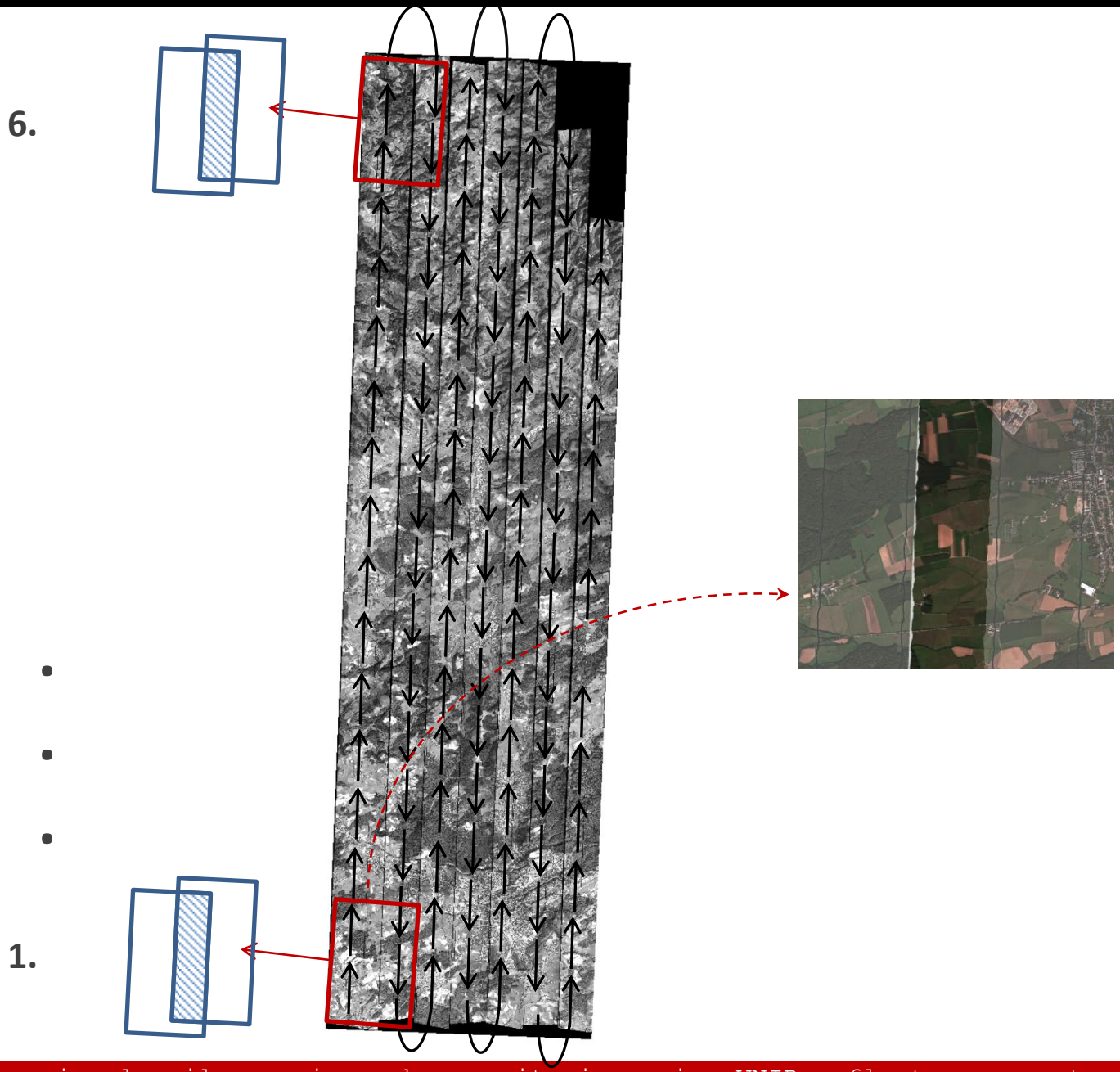
Overflight 16.09.2011, 7 flight lines, total number of 39 tiles

Weather conditions: some high altitude cirrus

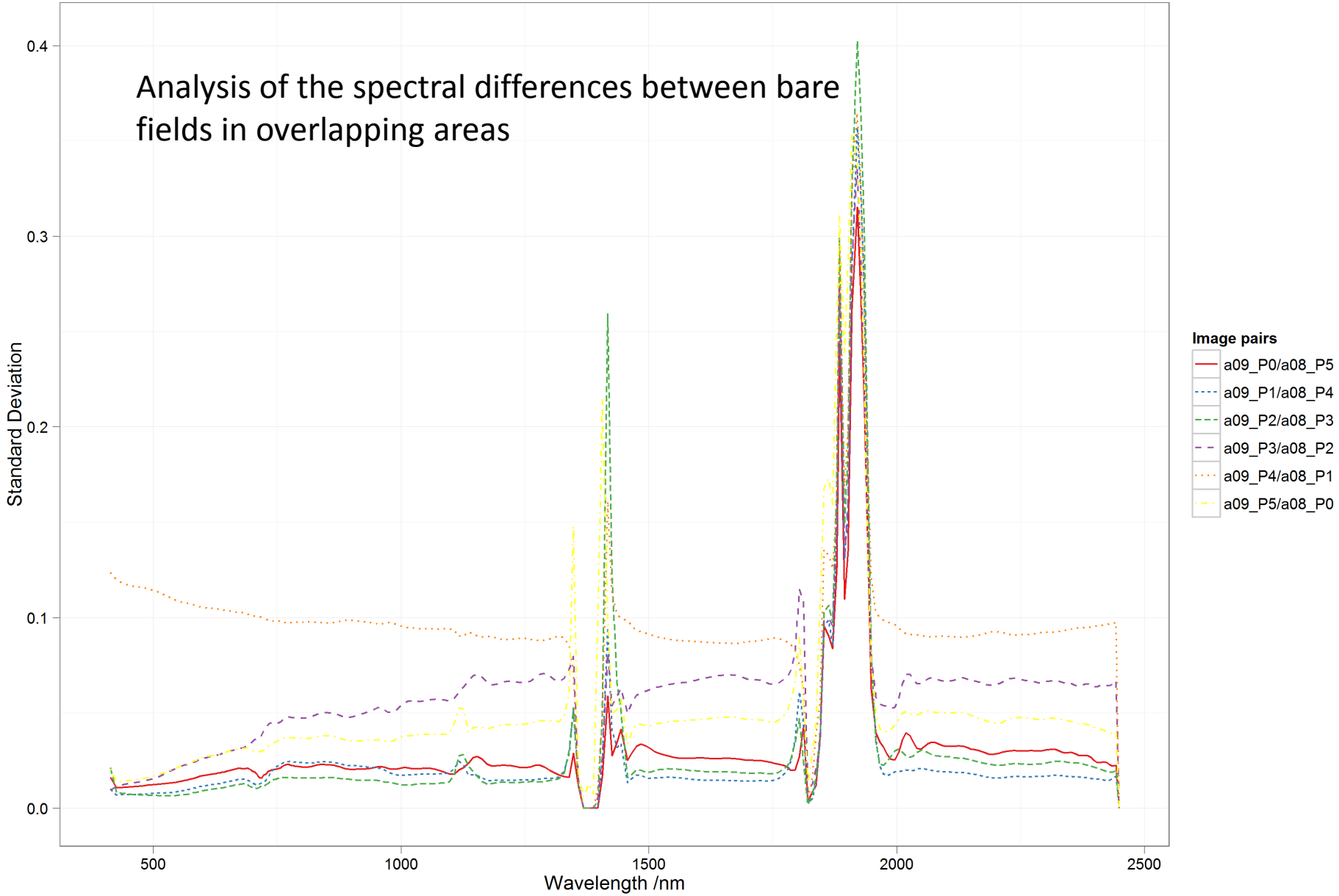
Atmospheric & geometric correction by the VITO + re-analysis by Tel-Aviv University with ACORN

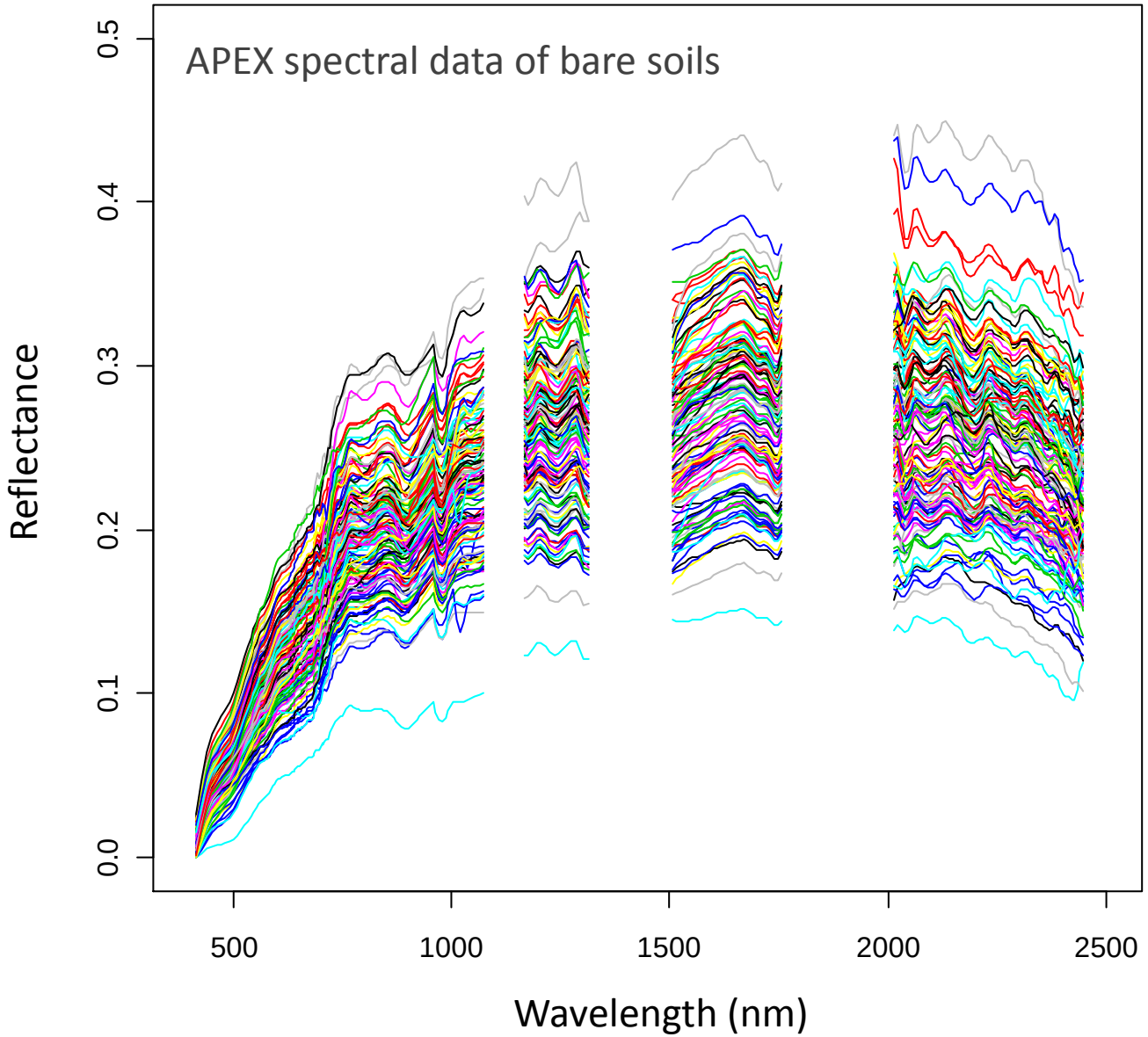



1.


6.
1.

Analysis of the spectral differences between bare fields in overlapping areas




APEX spectral data of bare soils
Reflectance
0.0
0.1
0.2
0.3
0.4
0.5
500
1000
1500
2000
2500
Wavelength (nm)

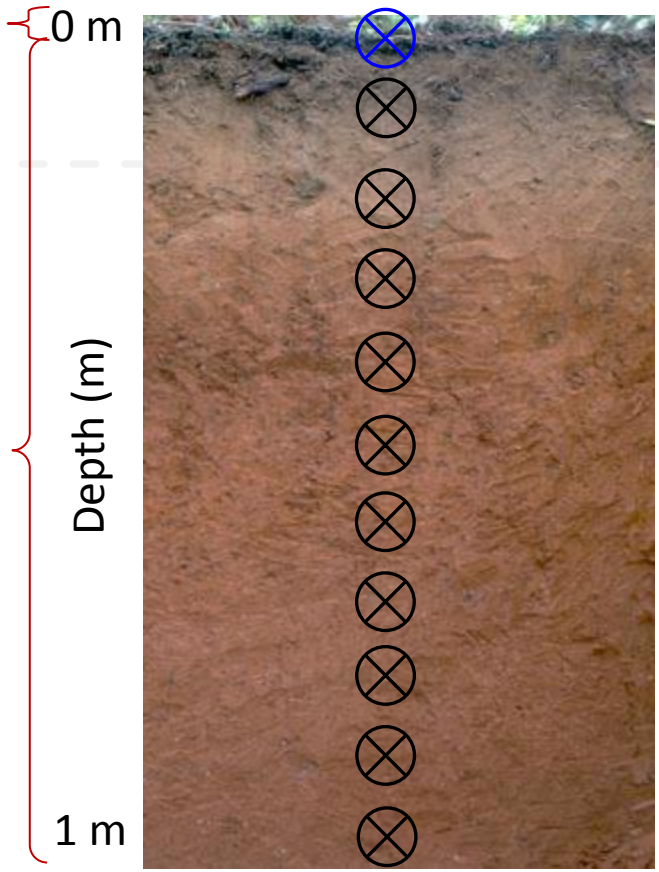
Basic strategy

2D

APEX DATA +
(Geomorphic features)

3D

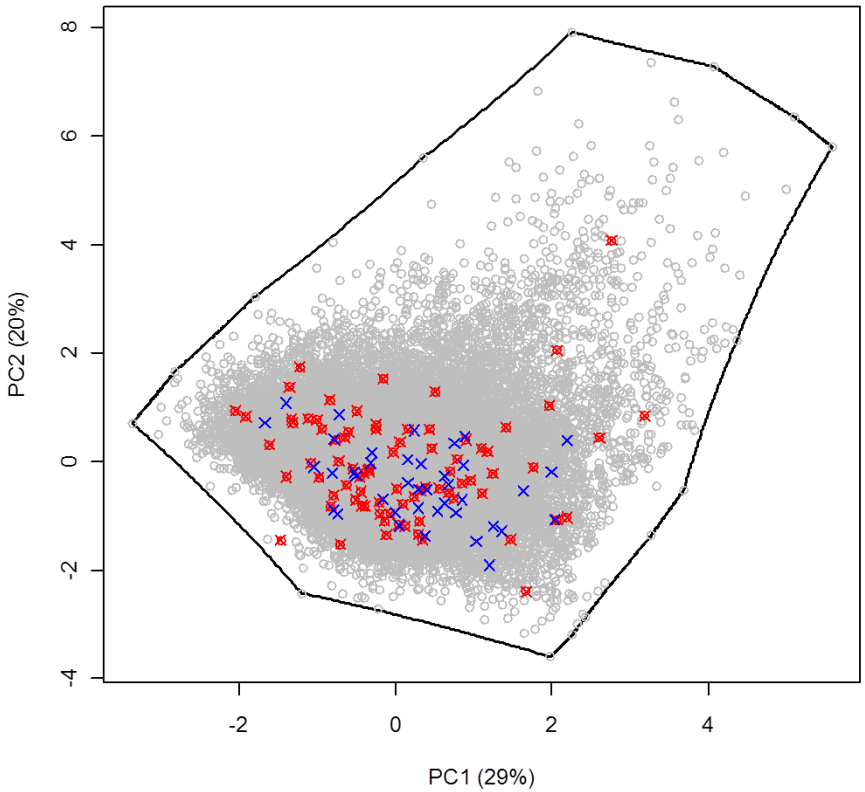
Geomorphic features



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)

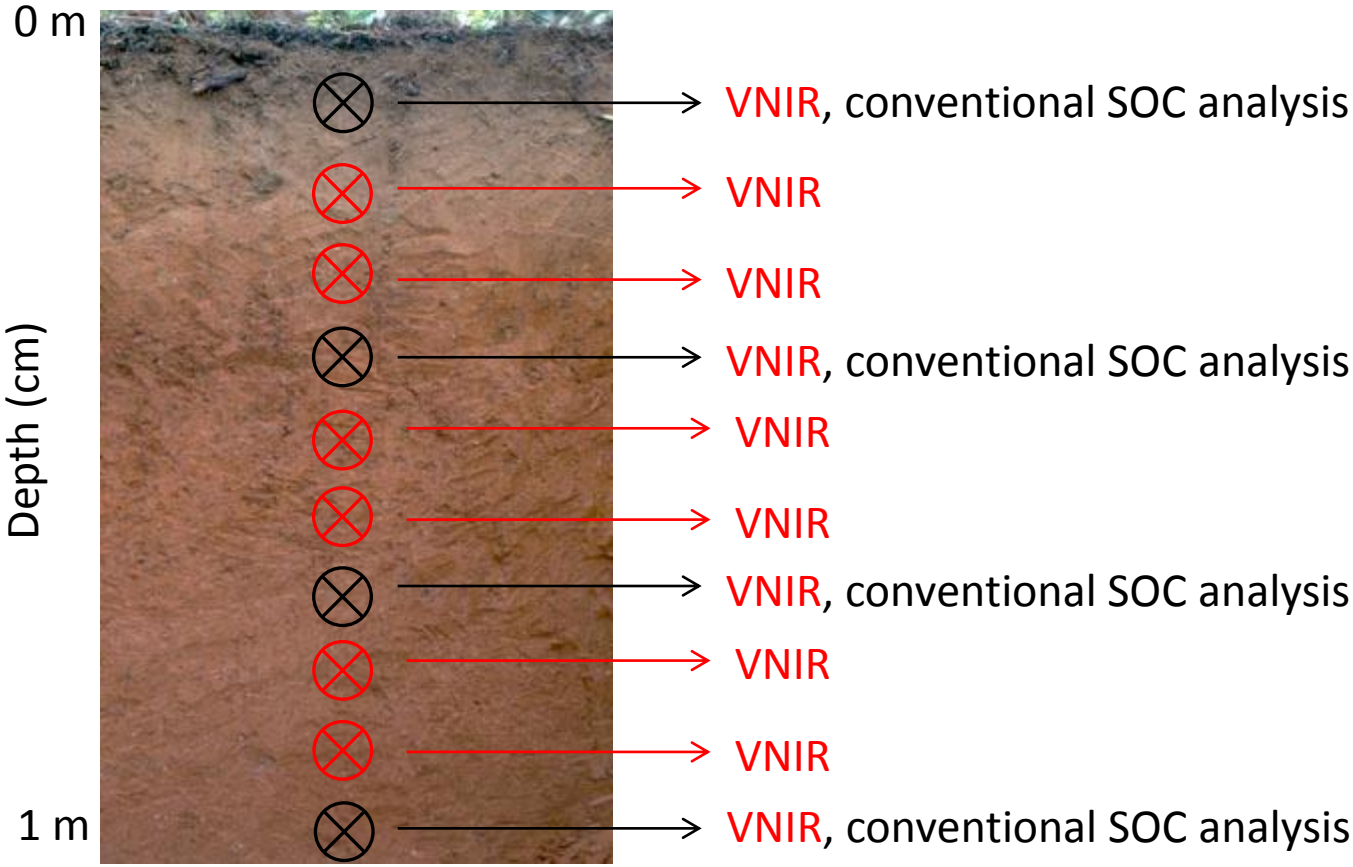


Calibration samples (*n*=90)
Validation samples (*n*=44)

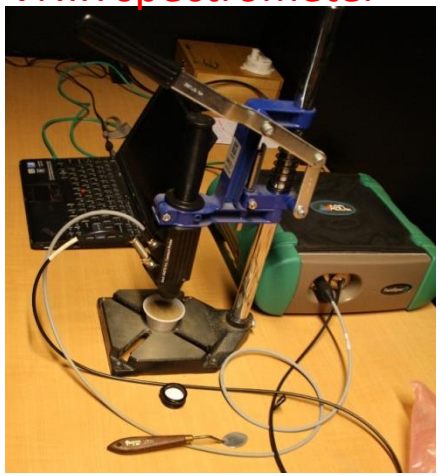
Strategy for SOC analysis of the calibration samples

40 % Conventional SOC analysis (C/N analyzer) and VNIR spectra

60 % Only VNIR spectra



VNIR spectrometer



C/N analyzer

Problem

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

Approach

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

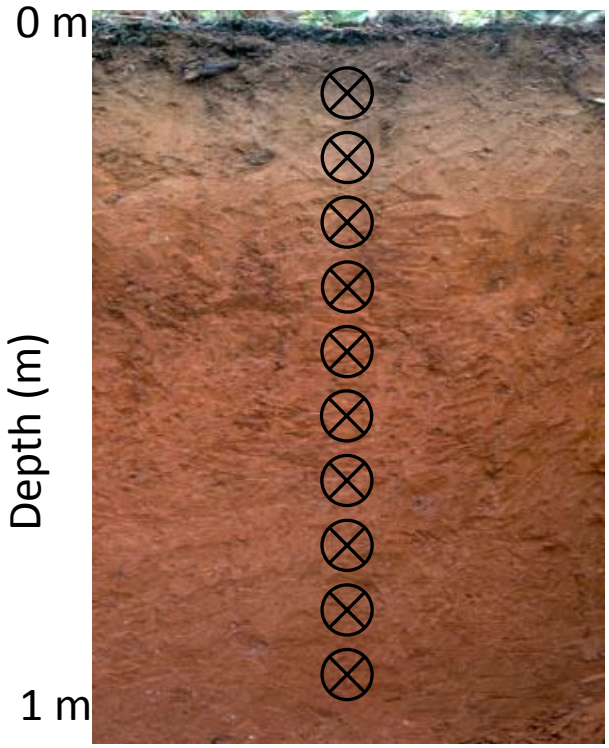
$$SOC = \boxed{f}(VNIR^{*}, \ldots)$$

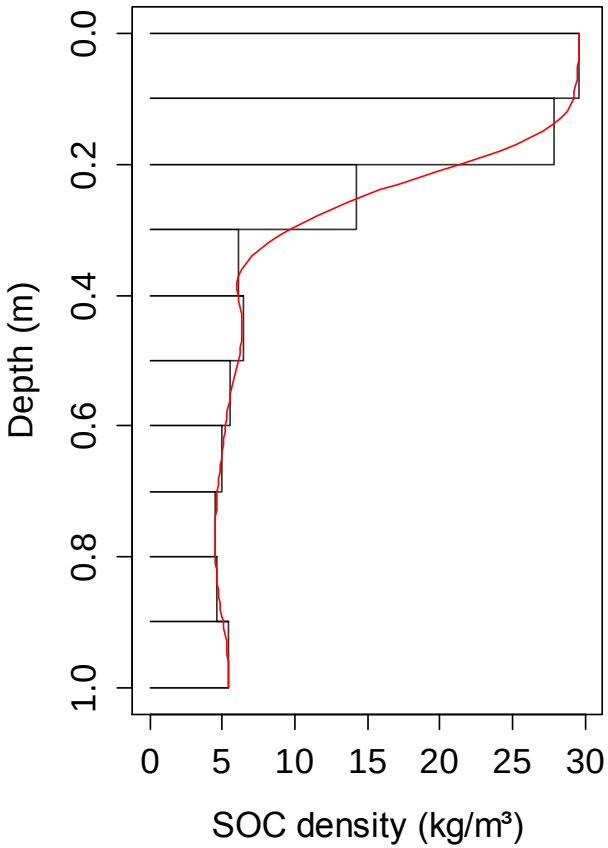
Data mining

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

Modeling depth distribution of soil carbon concentration…

Fitting mass conserving splines functions to the profiles





Depth functions were used to generate SOC information (of all the profiles) at 0.01 m vertical resolution

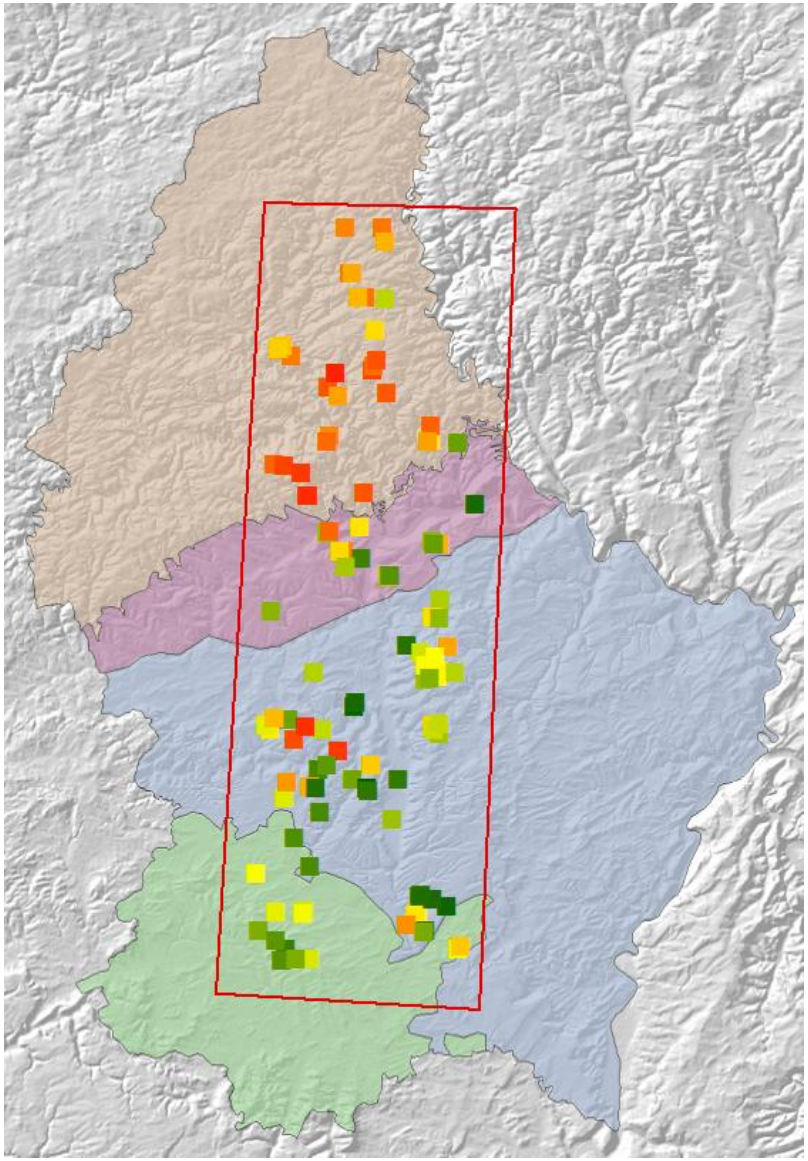
Spatial modeling of depth functions of soil organic carbon …

$$SOC_d = \boxed{f}\,(\text{Geomorphic f},\ldots) + \varepsilon_0 + \boxed{\varepsilon}$$

Random forests

$f\,(x, y)$

Part of the error which can be modeled by using the geographical information (x and y coordinates)



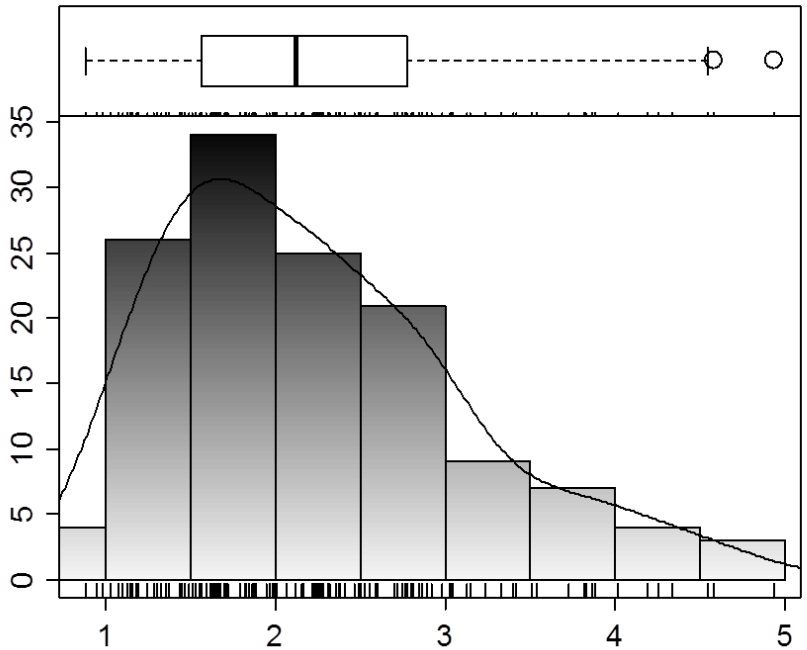
Agro-pedological regions

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

SOC, %

4.58

0.88

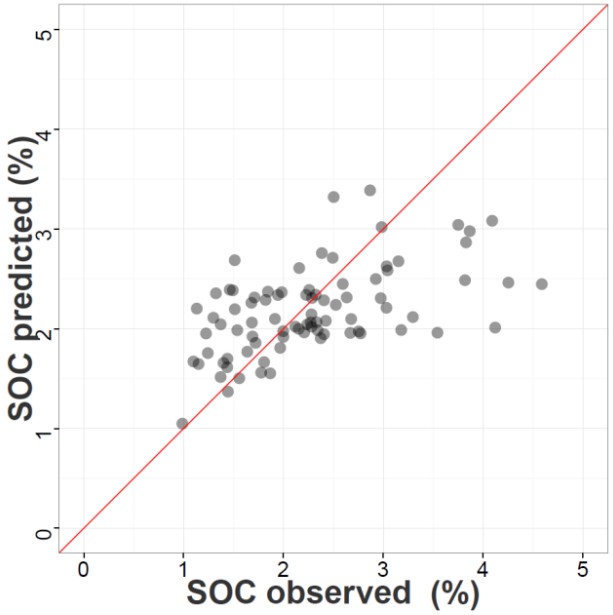


Prediction of surface SOC

No differences between terrain and spectra + terrain

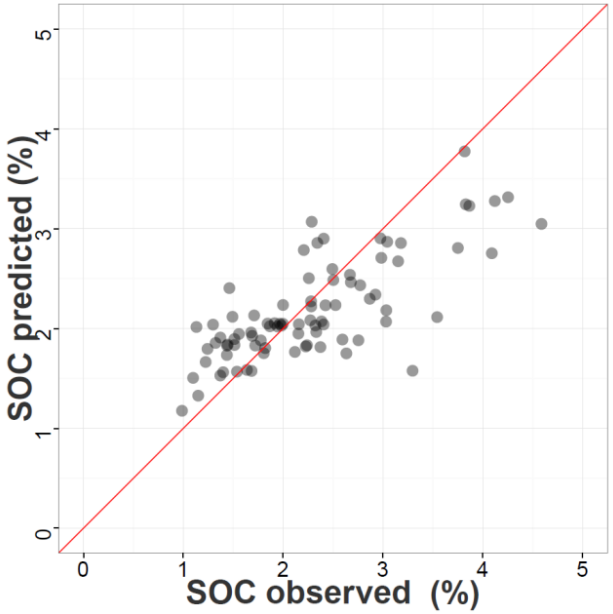
Spectra

RMSE = 0.69%
R^2=0.30



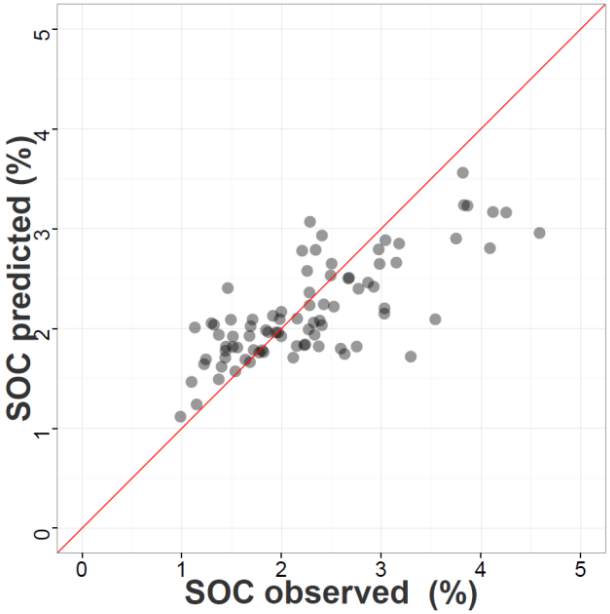
Terrain

RMSE = 0.55%
R^2=0.58

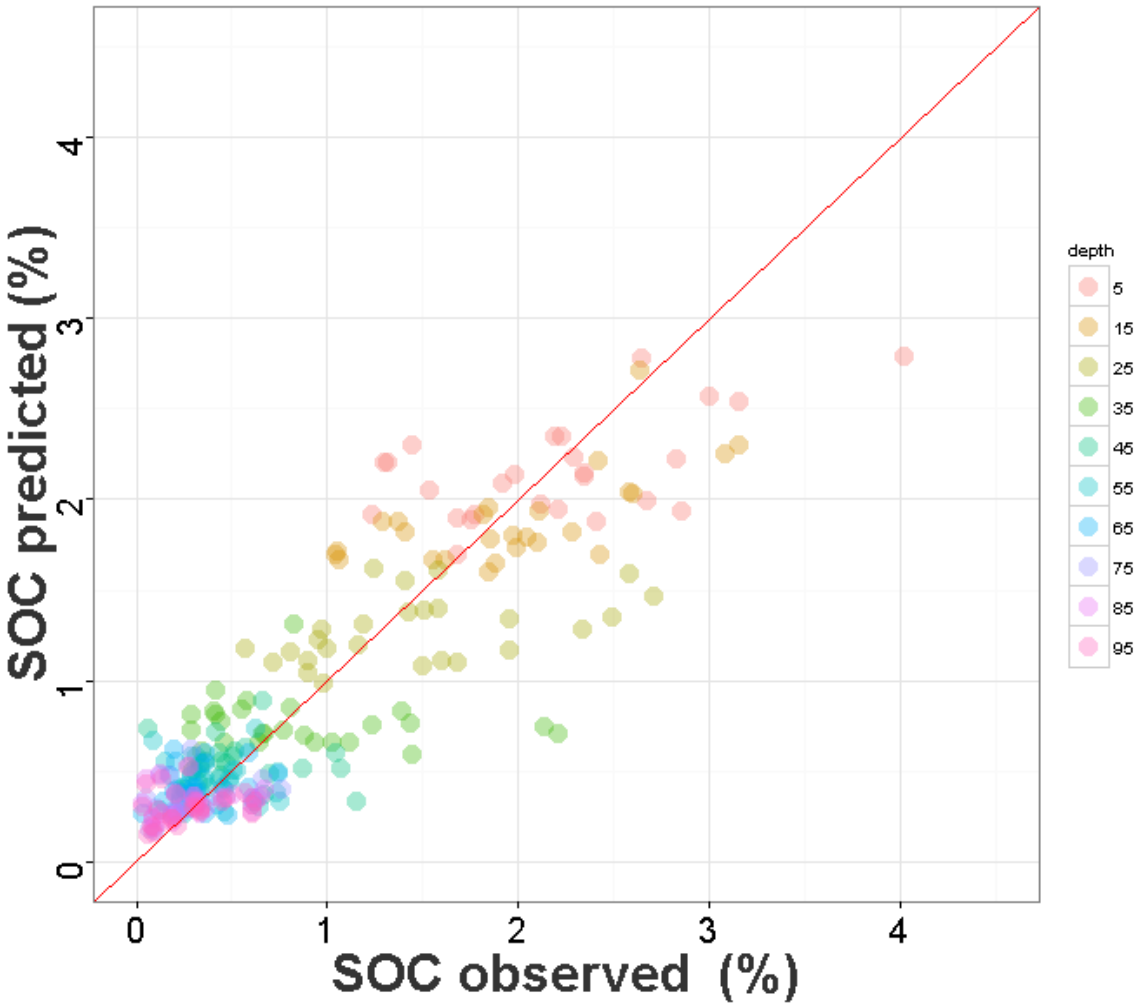


Spectra + Terrain

RMSE = 0.55%
R^2=0.58



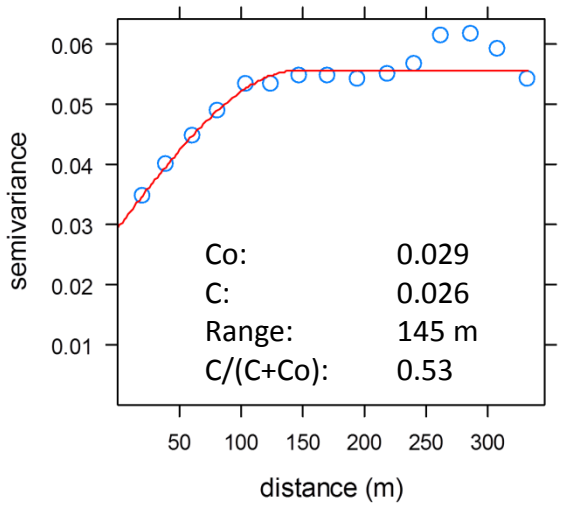
Prediction of sub-surface SOC using Random Forests – kriging

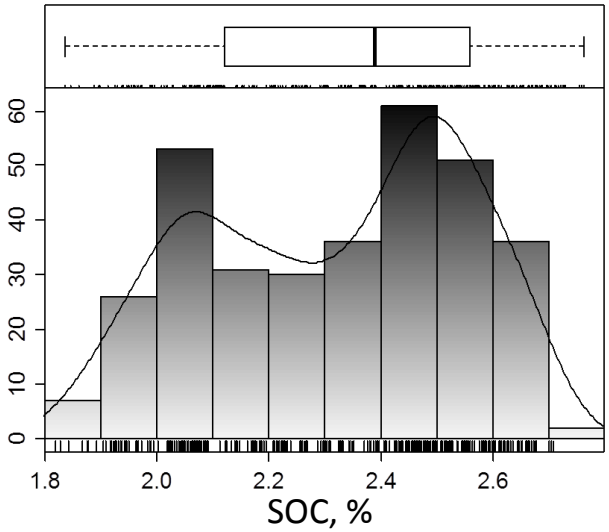


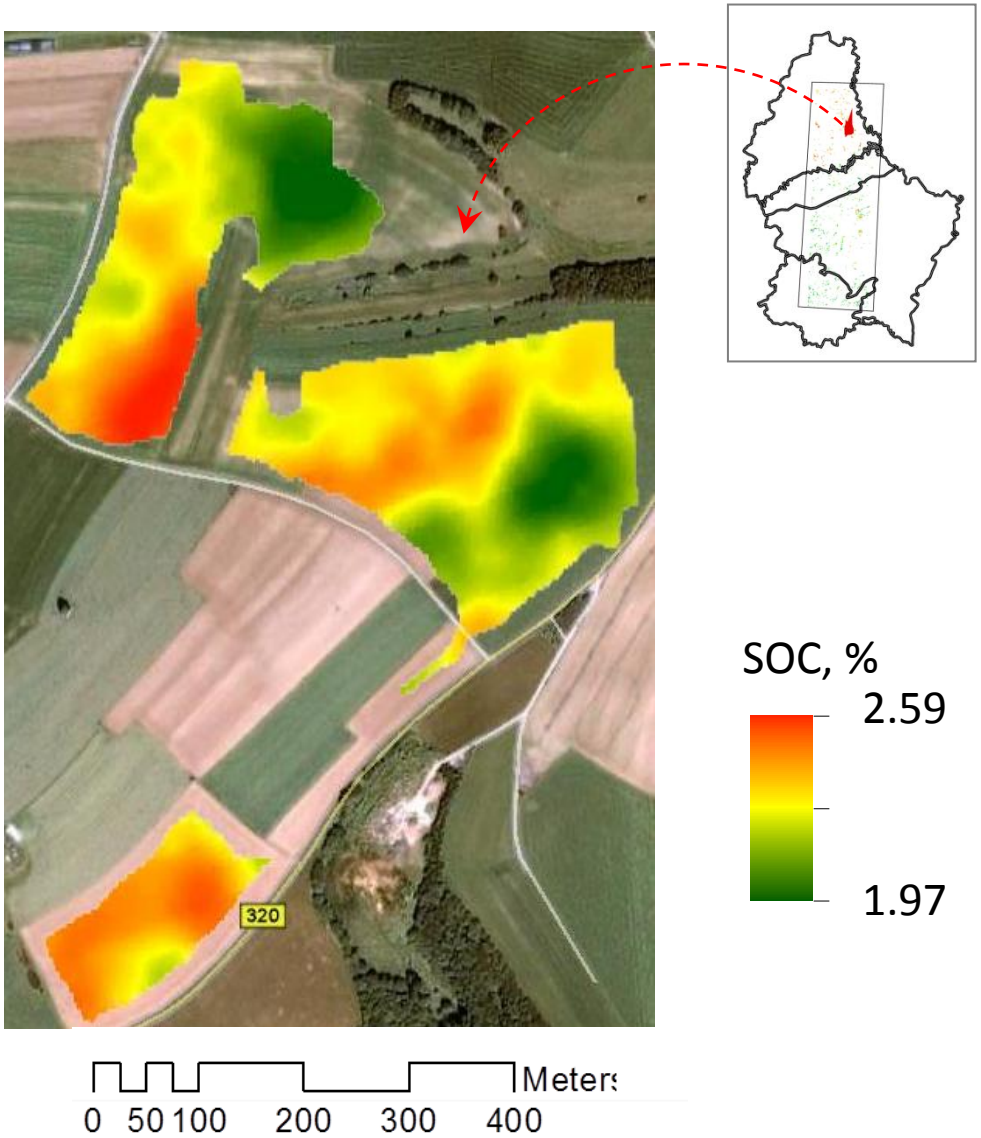
RMSE = 0.37%

R^2=0.79

Spatial prediction of SOC



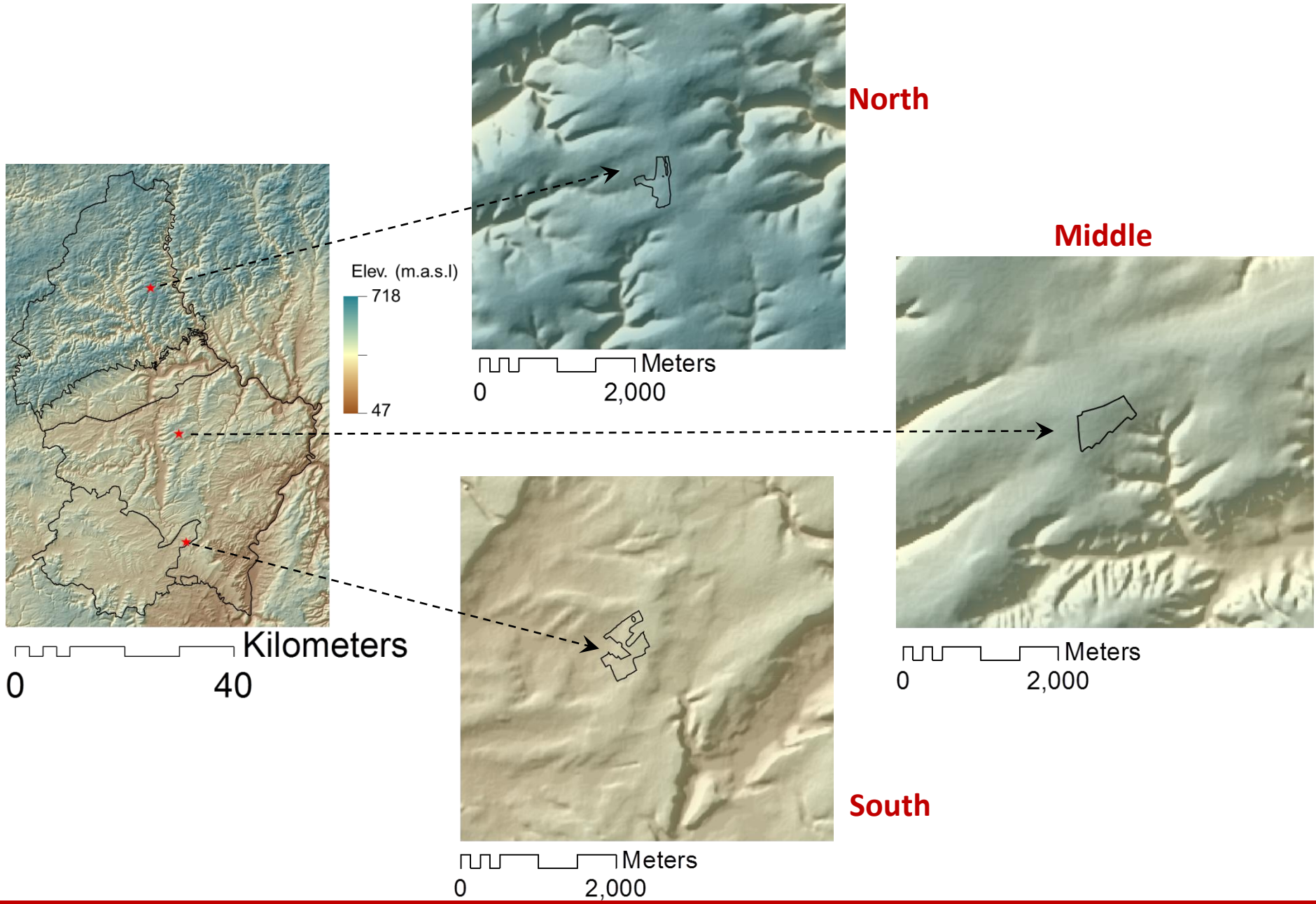




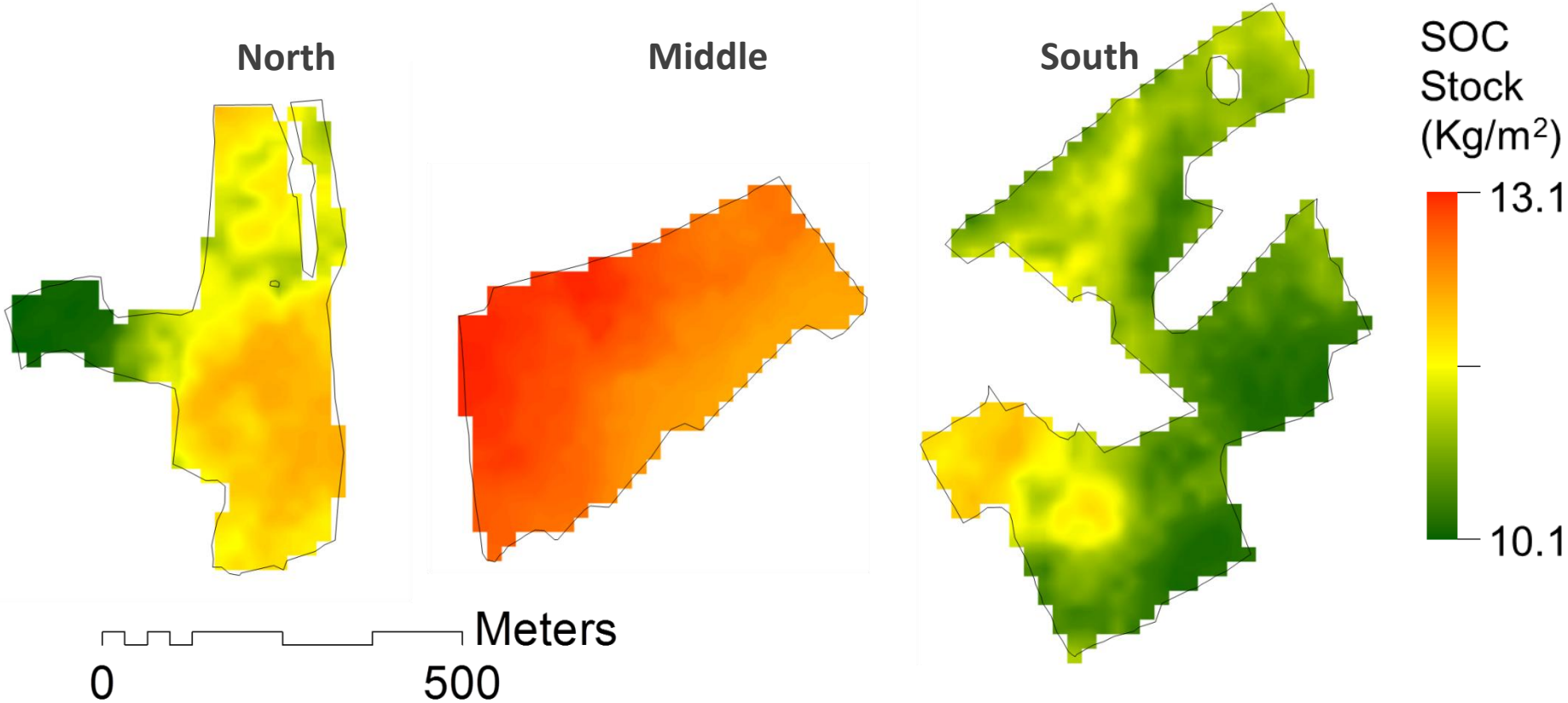
From SOC concentration (g C kg^{-1} soil)

to

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


North
Middle
South
Elev. (m.a.s.l)
718
47
Kilometers
0
40
Meters
0
2,000
Meters
0
2,000
Meters
0
2,000

SOC stocks



Despite croplands of the northern region of Luxembourg present the highest SOC concentrations at the topsoil layer, the SOC stocks are low due fact that these soils are thin and very gravelly.

Surface data was relatively well predicted using terrain attributes, spectra did not help that much

We used completely independent validation samples (random)!

We might have been over-optimistic in the design of the experiment by selecting a too large study area and flying under not perfect weather conditions, leading to inconsistent and noisy spectral data

Vertical distribution could have been better predicted if we would have constrained predictions with better surface data….