



Food and Agriculture
Organization of the
United Nations

GLOSOLAN
Soil spectroscopy
training workshops

Characterization of soil properties using the French national spectral libraries (Vis-NIR, NIR and MIR)

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Montpellier (France) / Bangalore (India)

Online
webinars



With the support of



Dominique Arrouays



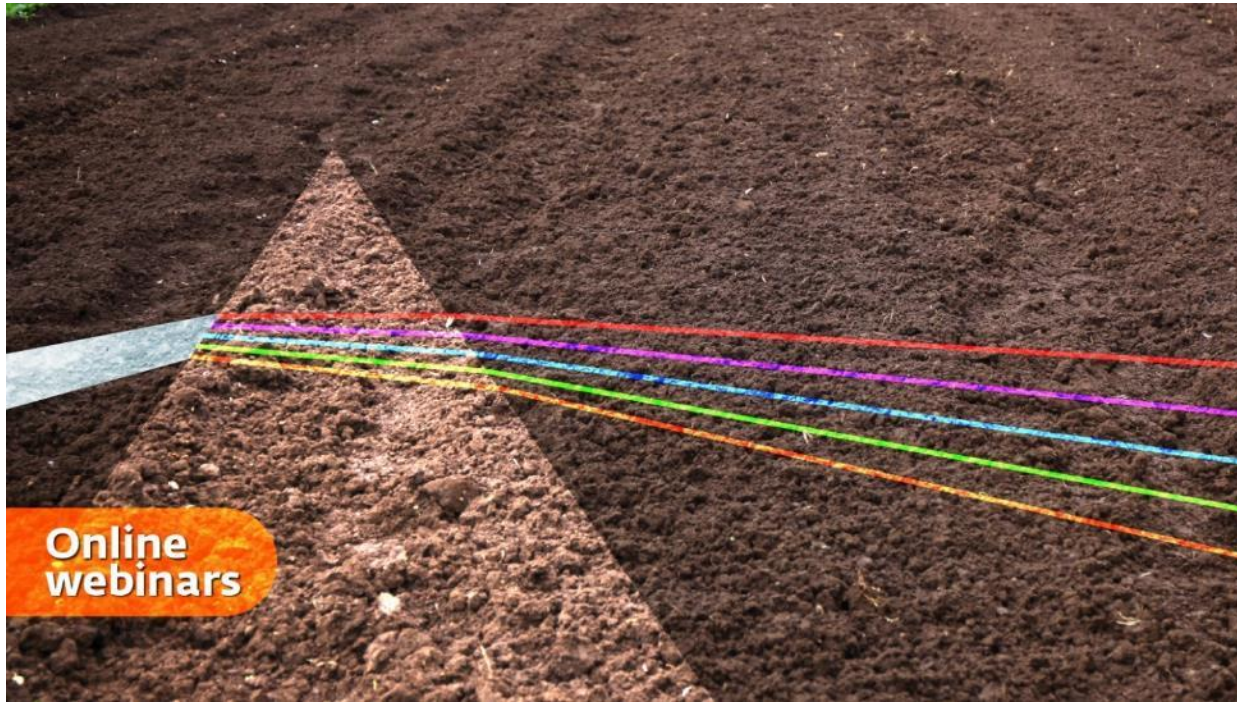
Claudy Jolivet



Bernard Barthès

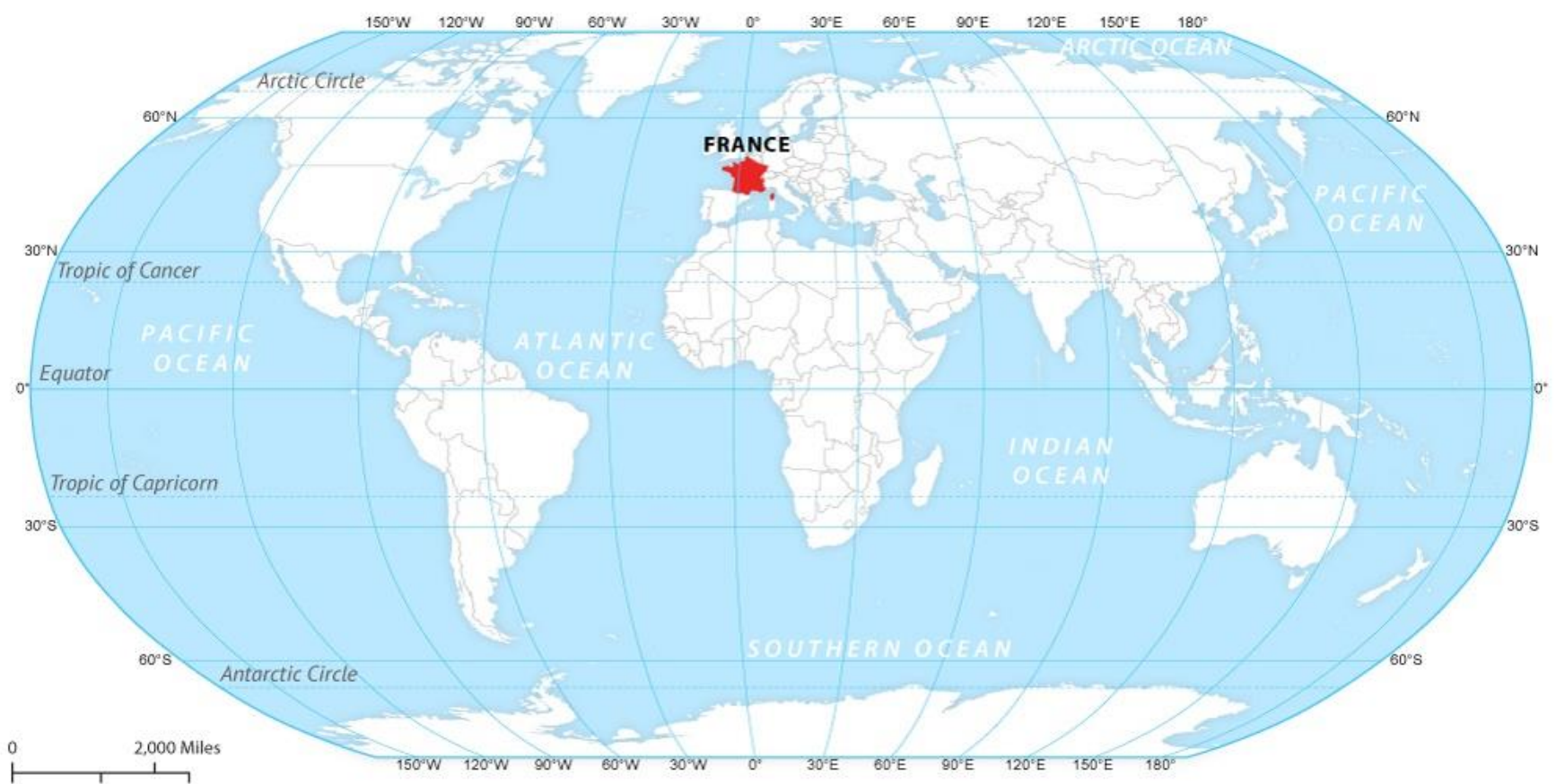


Patricia Moulin



CONTENTS

- The soil quality monitoring network for French soils (RMQS)
- Can we use the French spectral library for soil properties estimation
 - At National Scale (in France)?
 - At Regional Scale (in France)?
 - At Regional Scale (Outside of France)?



The soil quality monitoring network for French soils (RMQS)

A program funded and coordinated by the group of scientific interest SOL (Gis Sol)



for heritage and sustainable soil management



Toward a long-term monitoring of soil quality

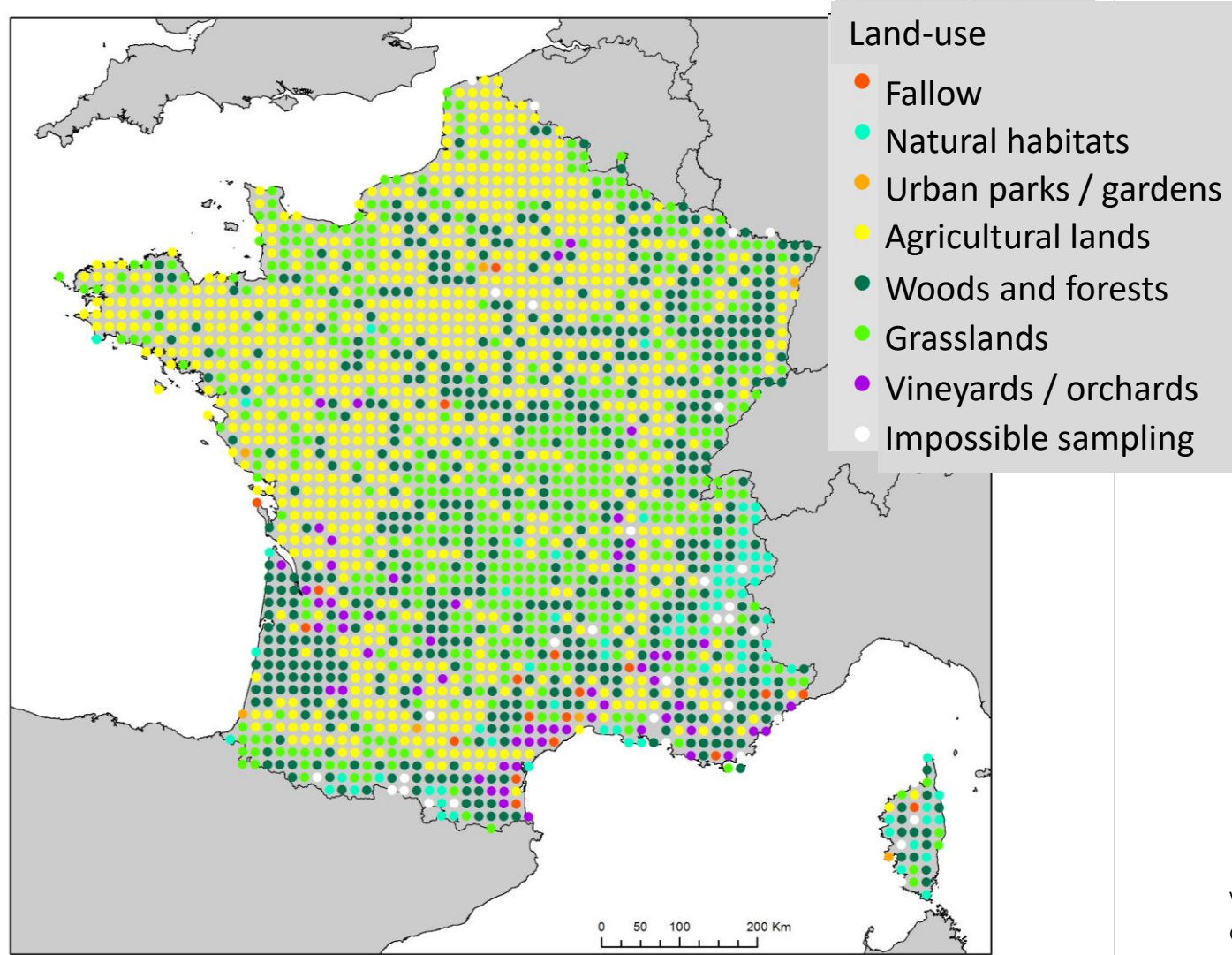


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- **National statement** (global statistic report on soil parameters evolution)
- **Mapping** (to get an instant picture of soil quality and detect gradients)
- **Warning** (early detection of unsuspected evolution)
- **Archiving** (to constitute a bank of soil samples)

Arrouays D., Jolivet C., Boulonne L., Bodineau G., Saby N. et Grolleau E., 2002 - Une initiative nouvelle en France : la mise en place d'un réseau multi-institutionnel de la mesure de la qualité des sols (RMQS). Comptes rendus de l'Académie d'Agriculture de Paris, 88, n° 5, pp. 93-103

A systematic network representative of French soils and land-uses



- 2200 sites
- located along a 16 x 16 km grid
- on continental France and overseas territories
- representative of French soils and land-uses
- resampled with 15 years interval

A new sampling campaign each 15 years



RMQS1 : 2000-2015

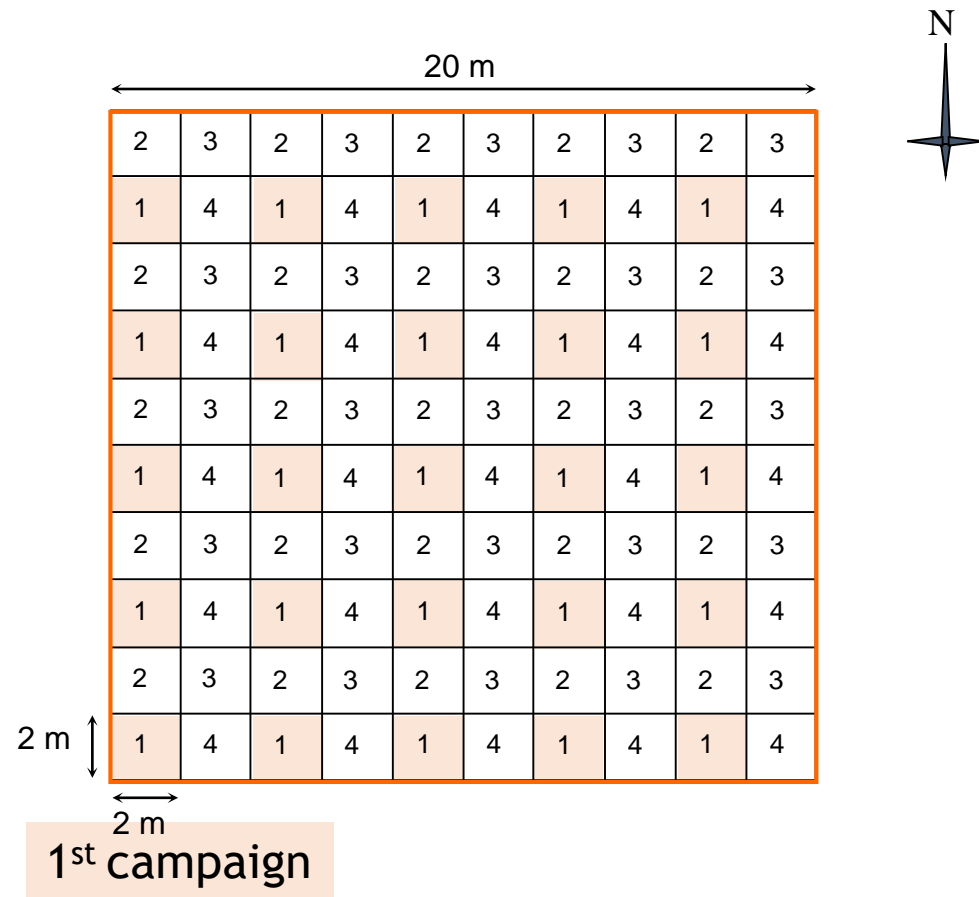
- Continental France : 2000-2009
- Overseas territories : 2006-2015
 - 2006 Guadeloupe
 - 2007 Martinique
 - 2012 Réunion & Mayotte
 - 2014-2015 French Guyana (coast)



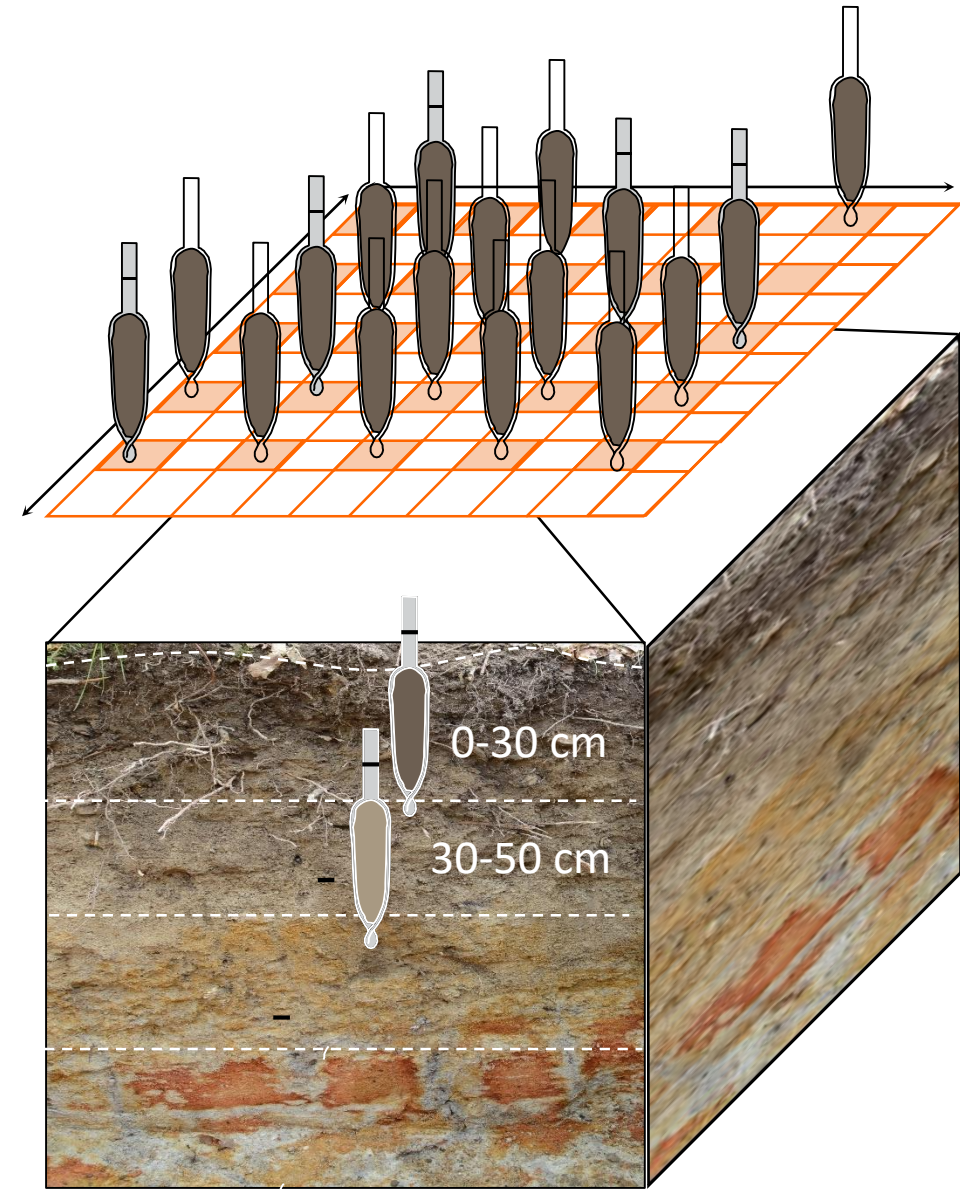
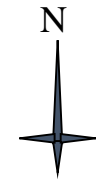
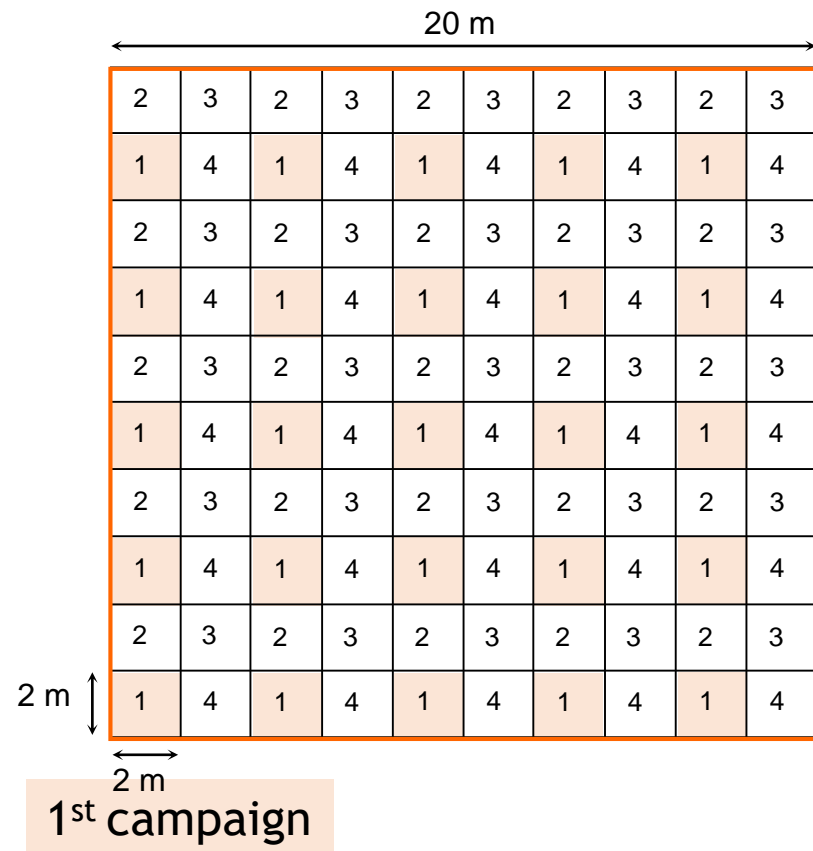
RMQS2 : 2016-2030

...

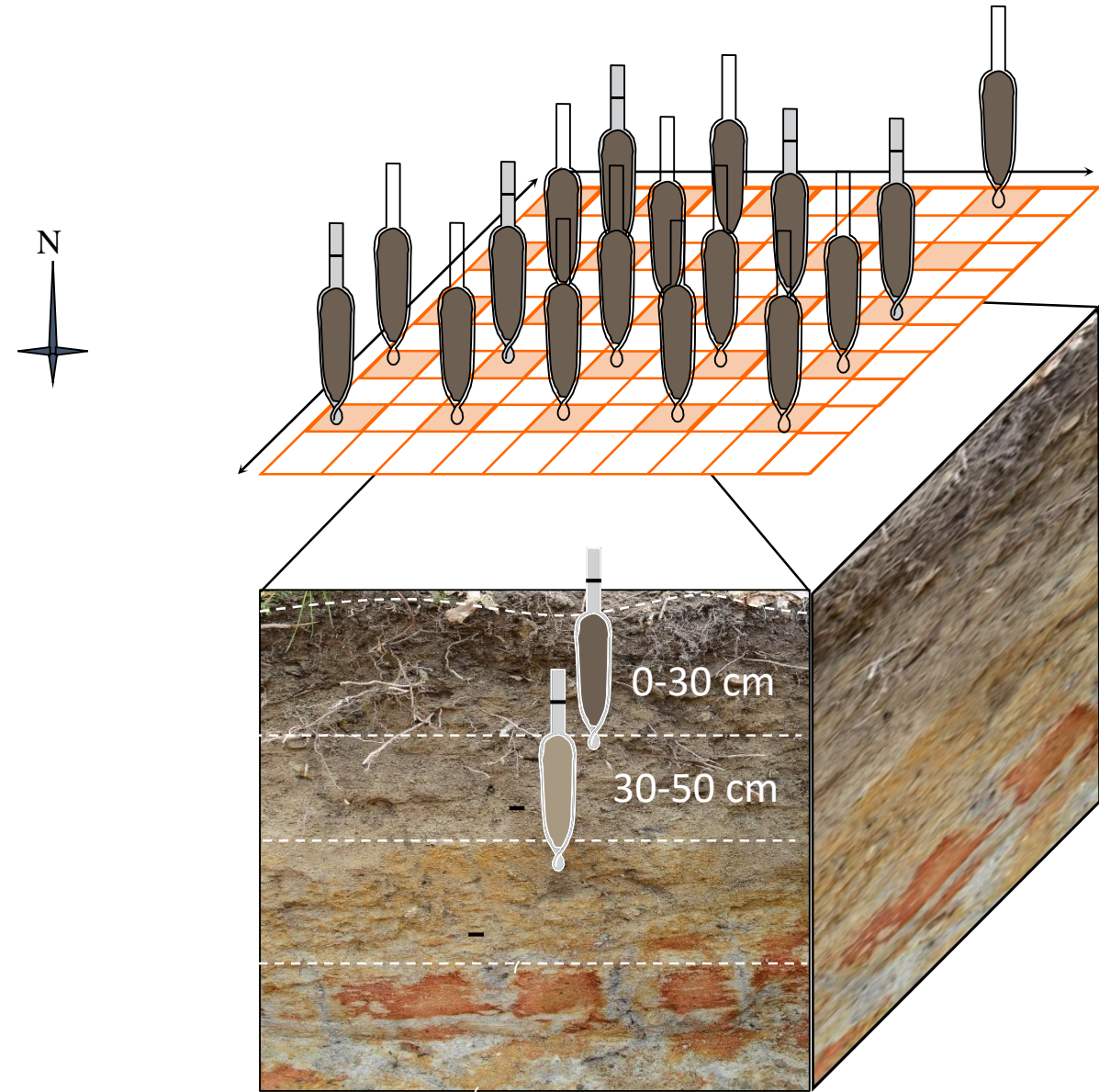
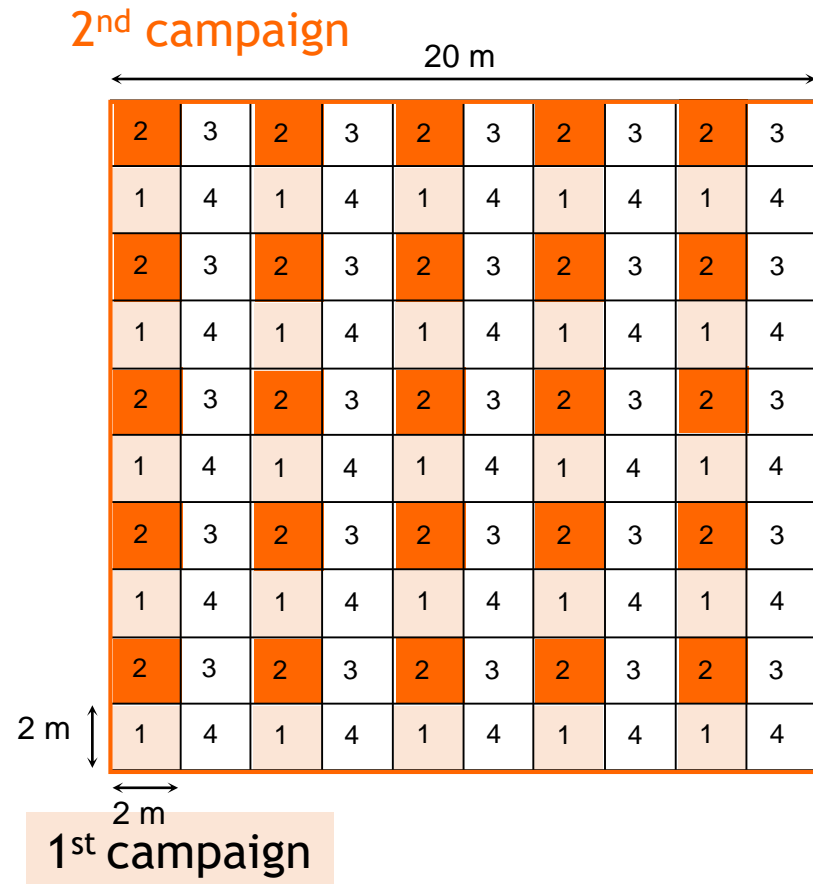
A sampling design dedicated to soil monitoring



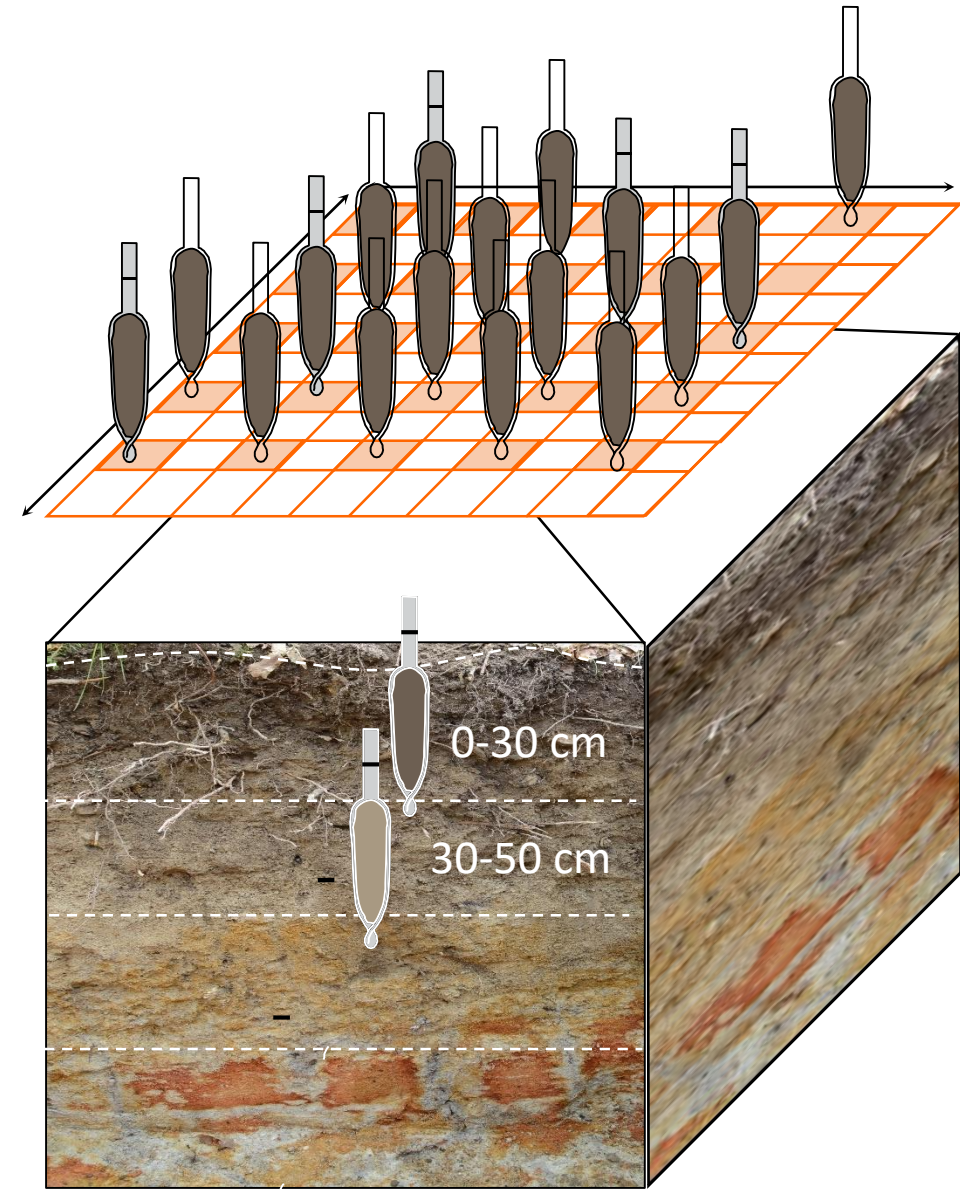
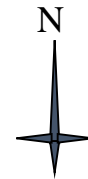
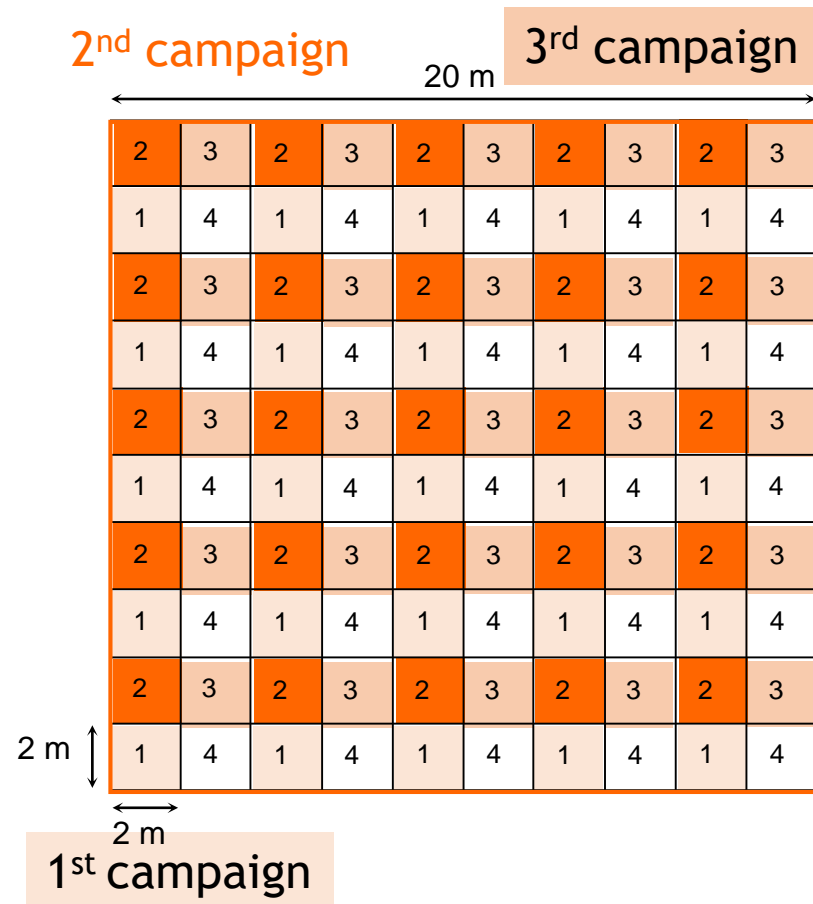
A sampling design dedicated to soil monitoring



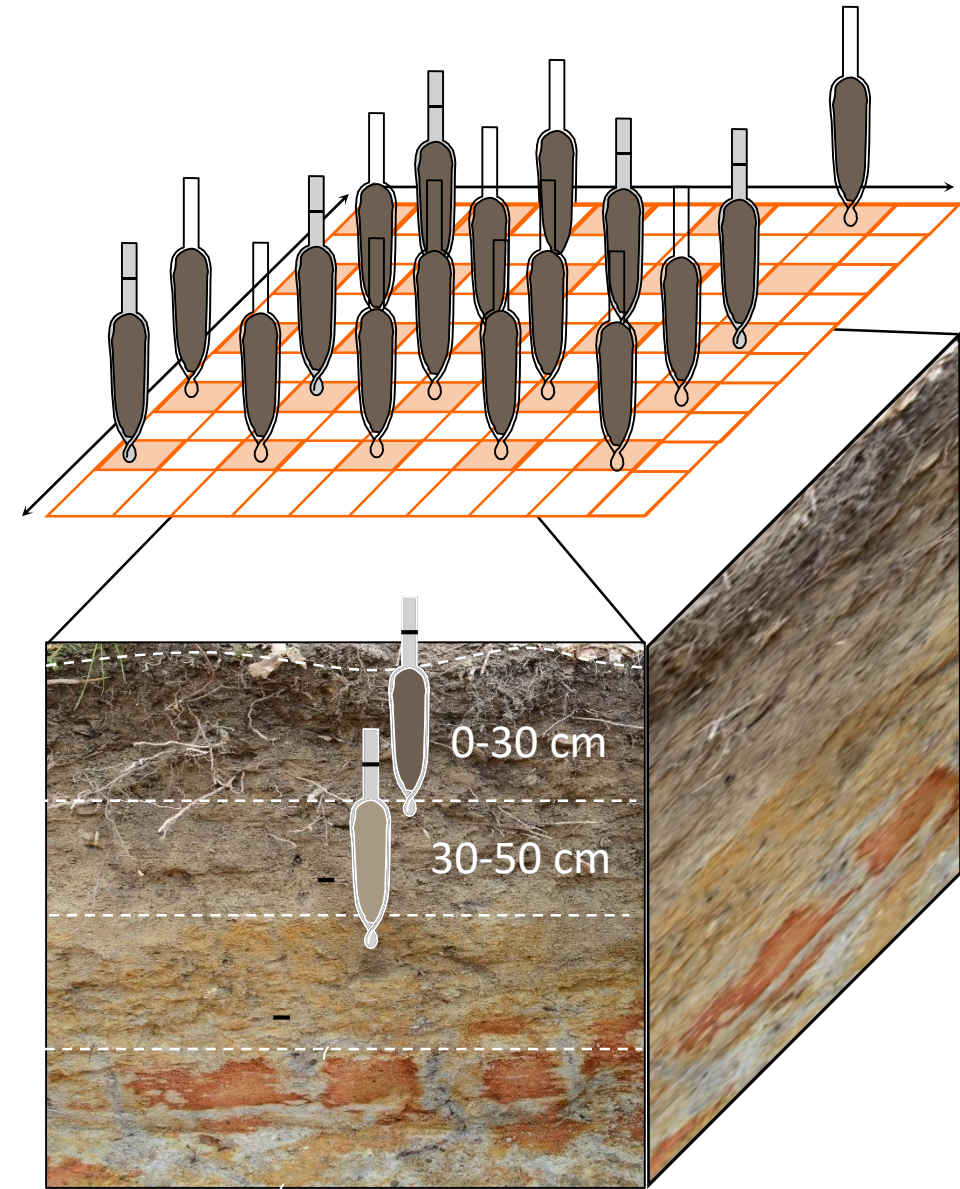
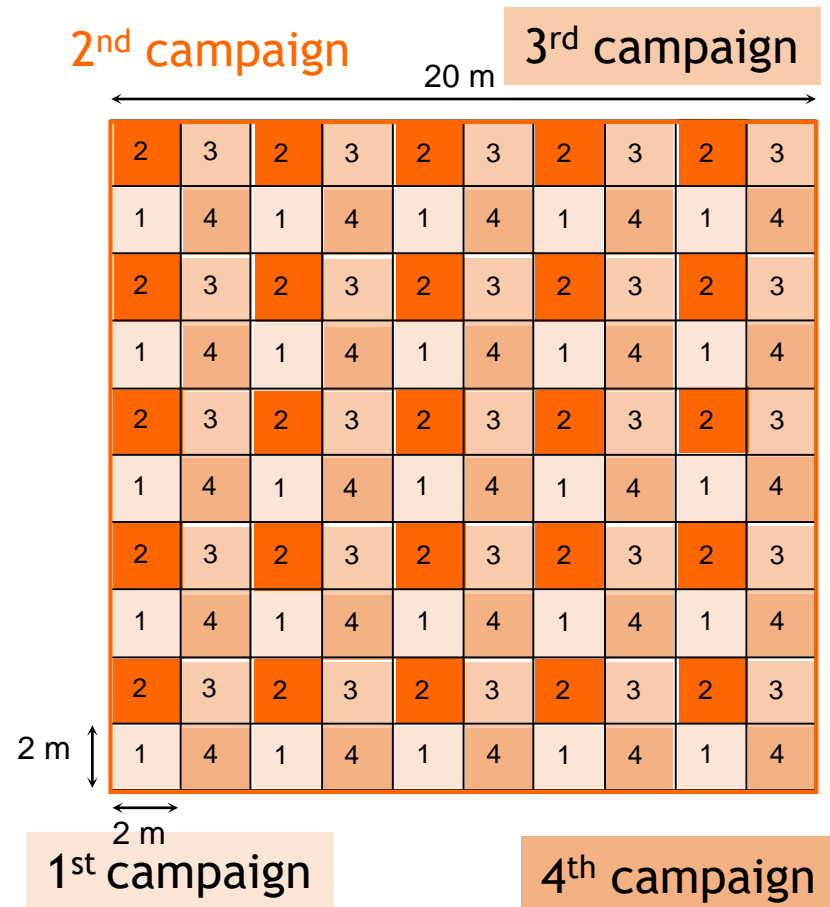
A sampling design dedicated to soil monitoring



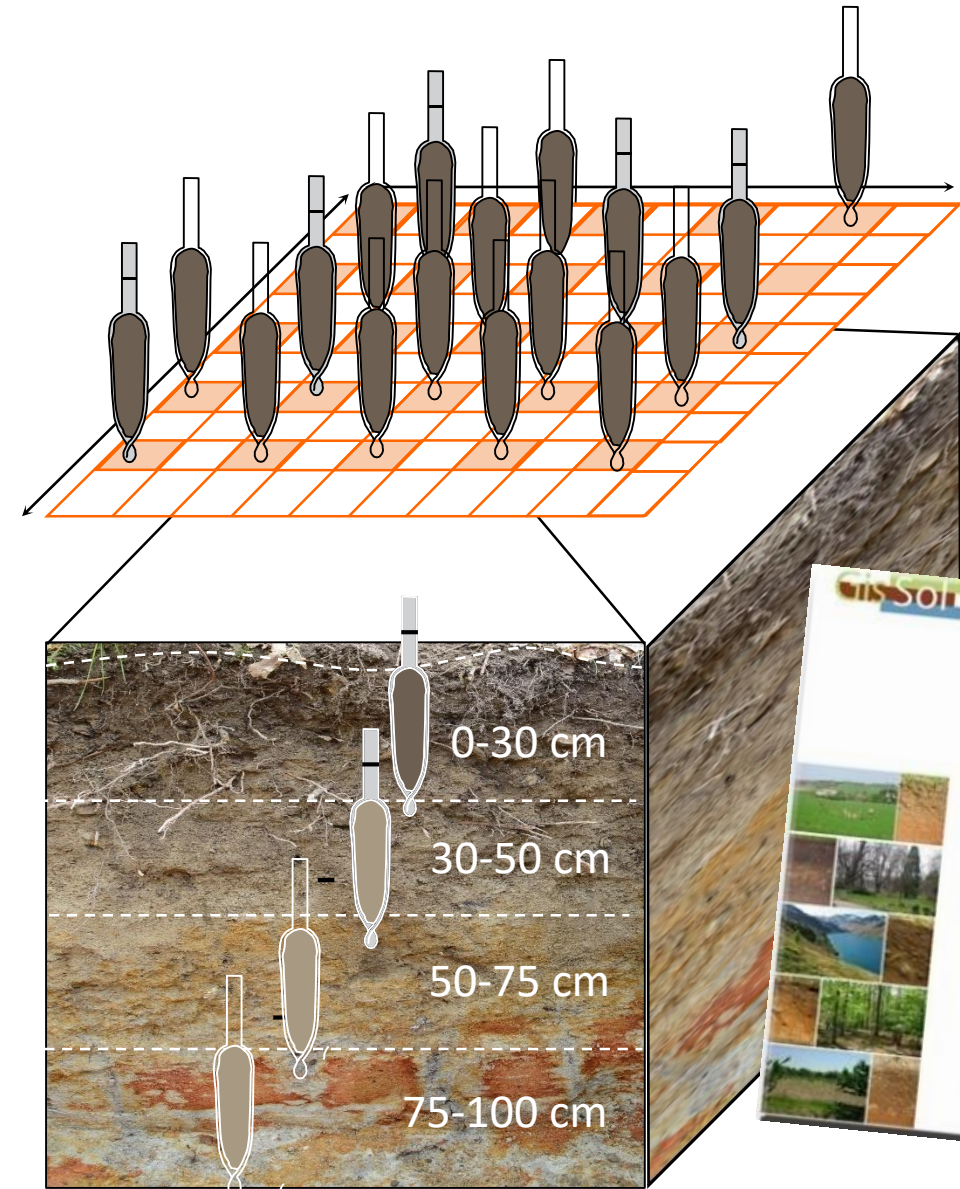
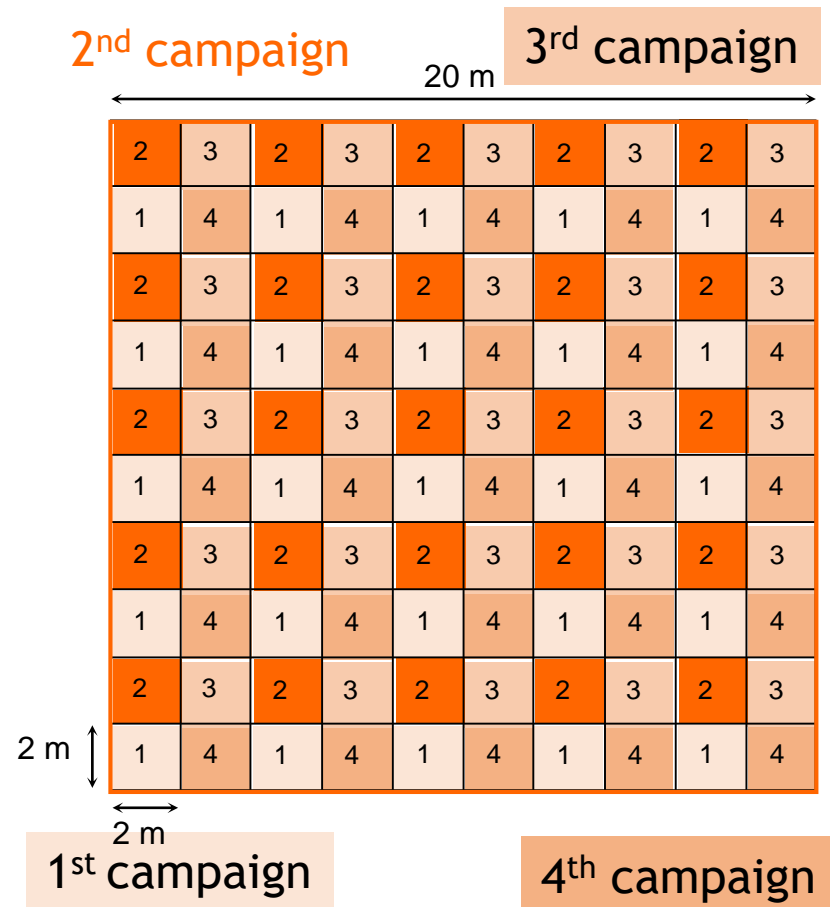
A sampling design dedicated to soil monitoring



A sampling design dedicated to soil monitoring



A sampling design dedicated to soil monitoring



English translation coming soon !



Data collection on the environment and practices

Environment & contamination sources



History & management practices = enquiries



INRA Unité Infosol - RMQS RMQS F 01B version 3 1105

5.4. Façons culturales, itinéraires techniques

1. Lister la succession des opérations pour les principales cultures de la succession culturale en cours : sous-solage, déchaumage, semis, hersage ou semis combiné, labour, (préciser la profondeur de travail du sol), passages pour fertilisation et traitements...
2. Préciser pour chaque opération l'outil utilisé, notamment pour les travaux du sol.
3. Préciser également la période ou date d'intervention.

1^{ère} culture : *blé*.....année : *2005*..... précédent : *blé*.....

Opérations	Date	Outil-méthode	Profondeur du travail du sol
Déchaumage (2 passages)	août	outil à dents et disques	
Fertilisation PK	septembre	épandeur centrifuge	
Semis	//	hense rotative et semoir	travail réduit du sol
Roulage	//	rouleau ondulé	
6 traitements (herbicide, fongicide...)	sept. à octobre	pulvérisateur	
Fertilisation N, S	janvier	épandeur centrifuge	
3 traitements fongicide	mars	pulvérisateur	
Récolte	juillet	moiss. - batteuse	
Broyage des tiges	août		

2^{ème} culture : *blé*.....année : *2004 et 2000*..... précédent : *betterave*.....

Opérations	Date	Outil-méthode	Profondeur du travail du sol
Déchaumage (2 passages)	oct ou nov	outil à dents + disque	
Semis	oct ou nov	hense rotative + semoir	
6 traitements	déc à juin	pulvérisateur	
4 passages fertilisation (N, S)	janv. à avril	"	
Récolte	juillet	moiss. batteuse	
Récolte fèves	août	prese - roundbaler	

→ essential data rarely collected on soil monitoring networks

A complete analytical menu for soil characterisation

- **Soil attributes**

- Particle size distribution, pH, C, N, P, CEC, exchangeable cations, major elements, etc.

- **Hydric properties**

- Soil water retention

- **Contaminants & human health**

- Traces elements: As, Cd, Co, Cr, Cu, Hg, Mo, Ni, Pb, Tl, Zn
- organic pollutants: HAP, PCB, dioxines, furanes, OCP, herbicides
- Pathogenic microorganisms

- **Carbon & climate change**

- Deep organic carbon stocks $\leq 1\text{m}$
- Particulate organic matter
- Organic matter quality: Black carbon, Glomaline

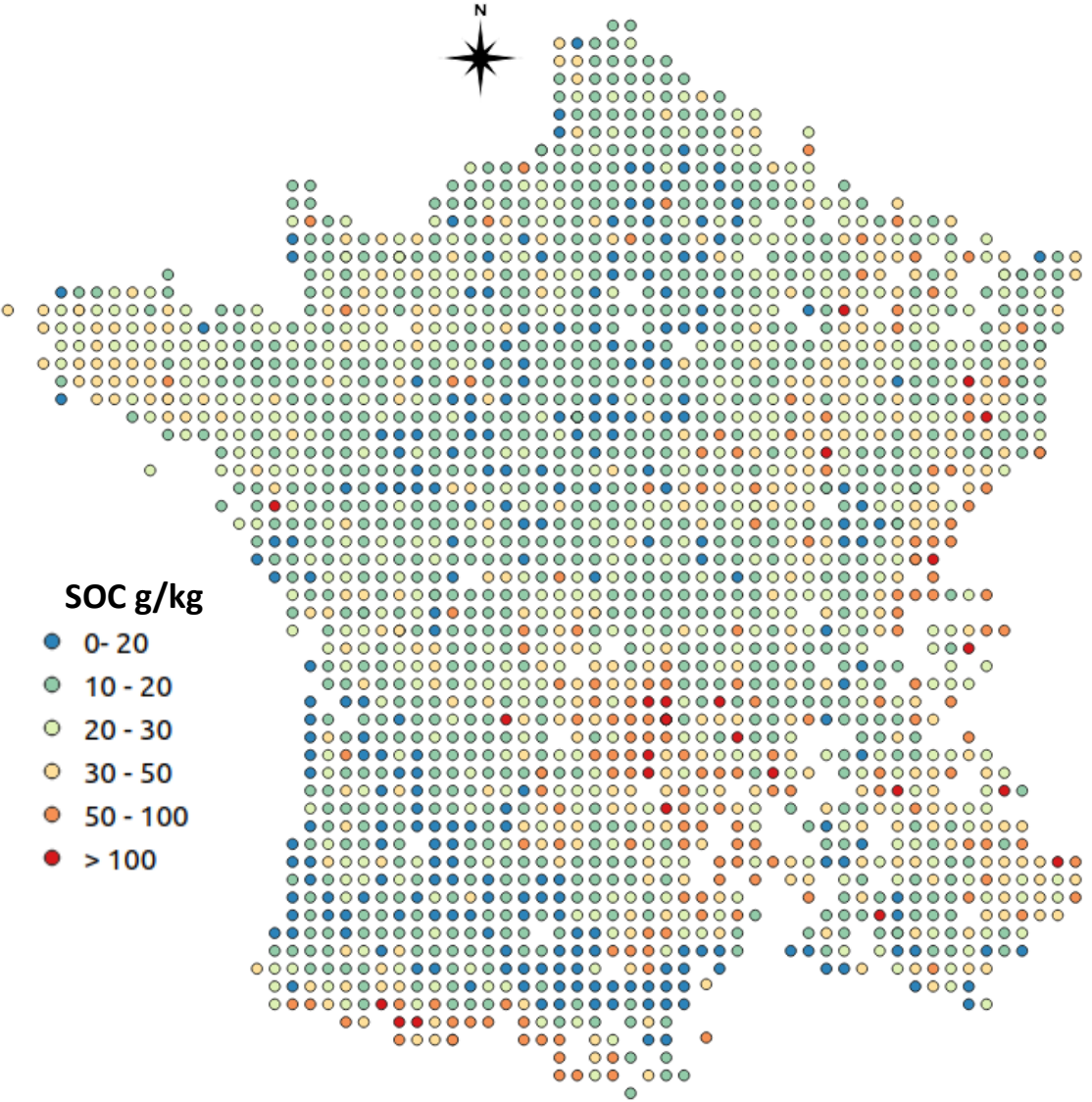
- **Soil biodiversity**

- Microbial richness & diversity by DNA extraction (Génosol)
- Enzymatic activity (BioChemEnv)

- **Vis-NIRS, NIRS, MIRS**

SOC

(Collected at 0-30 cm depth)

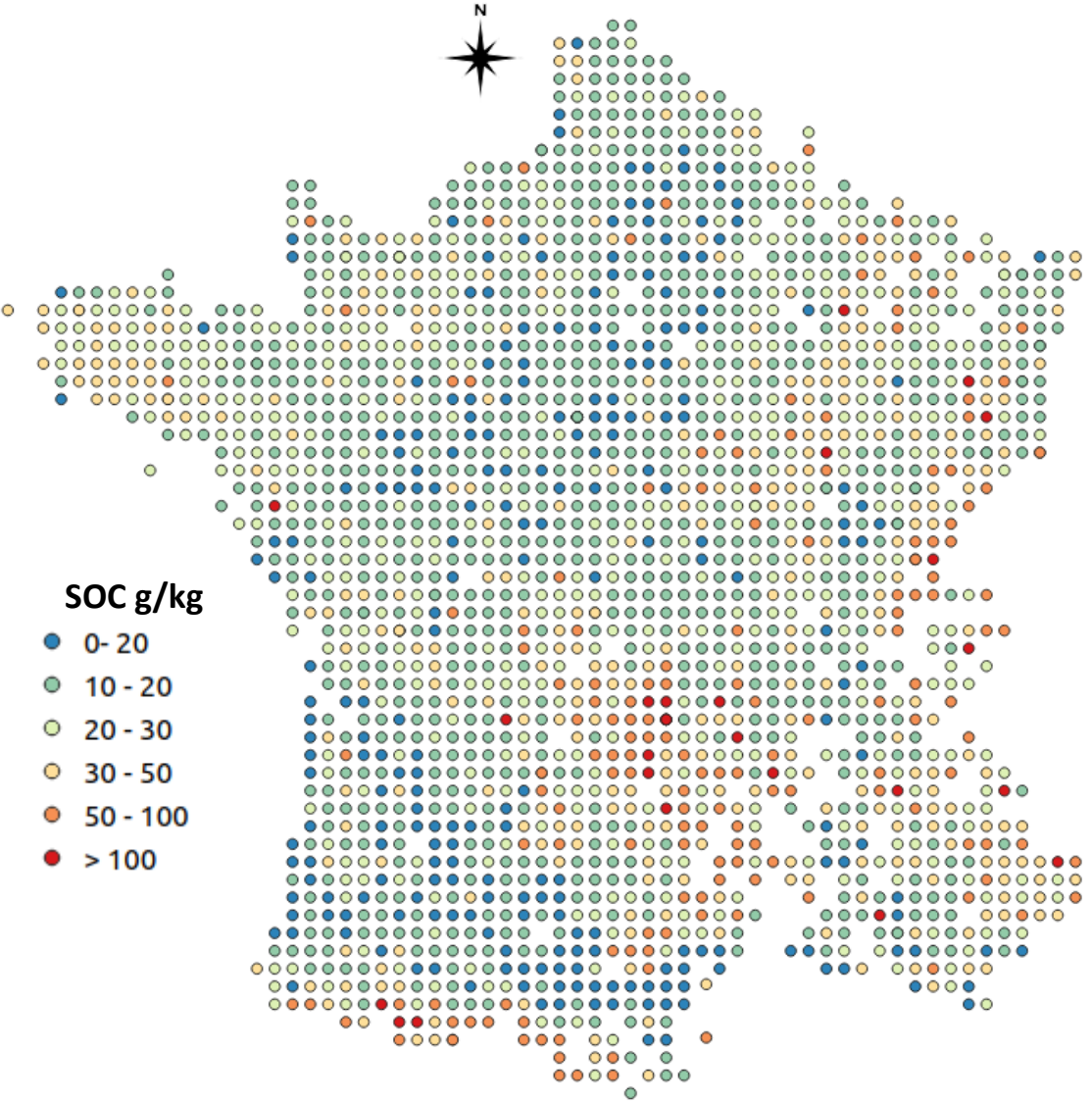


SOC g/kg

- 0-20
- 10-20
- 20-30
- 30-50
- 50-100
- > 100

SOC

(Collected at 0-30 cm depth)

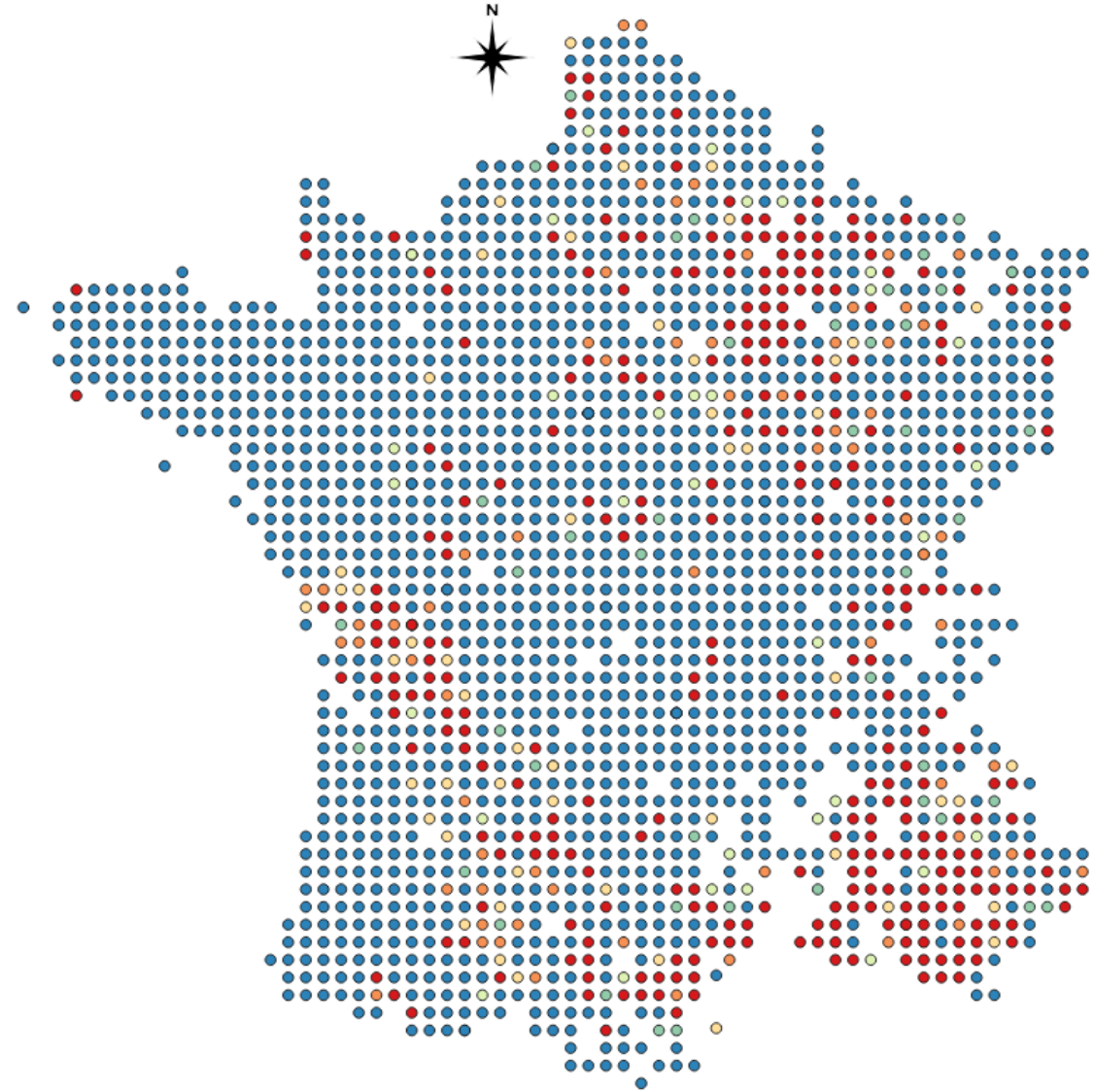


SOC g/kg

- 0 - 20
- 10 - 20
- 20 - 30
- 30 - 50
- 50 - 100
- > 100

SIC

(Collected at 0-30 cm depth)

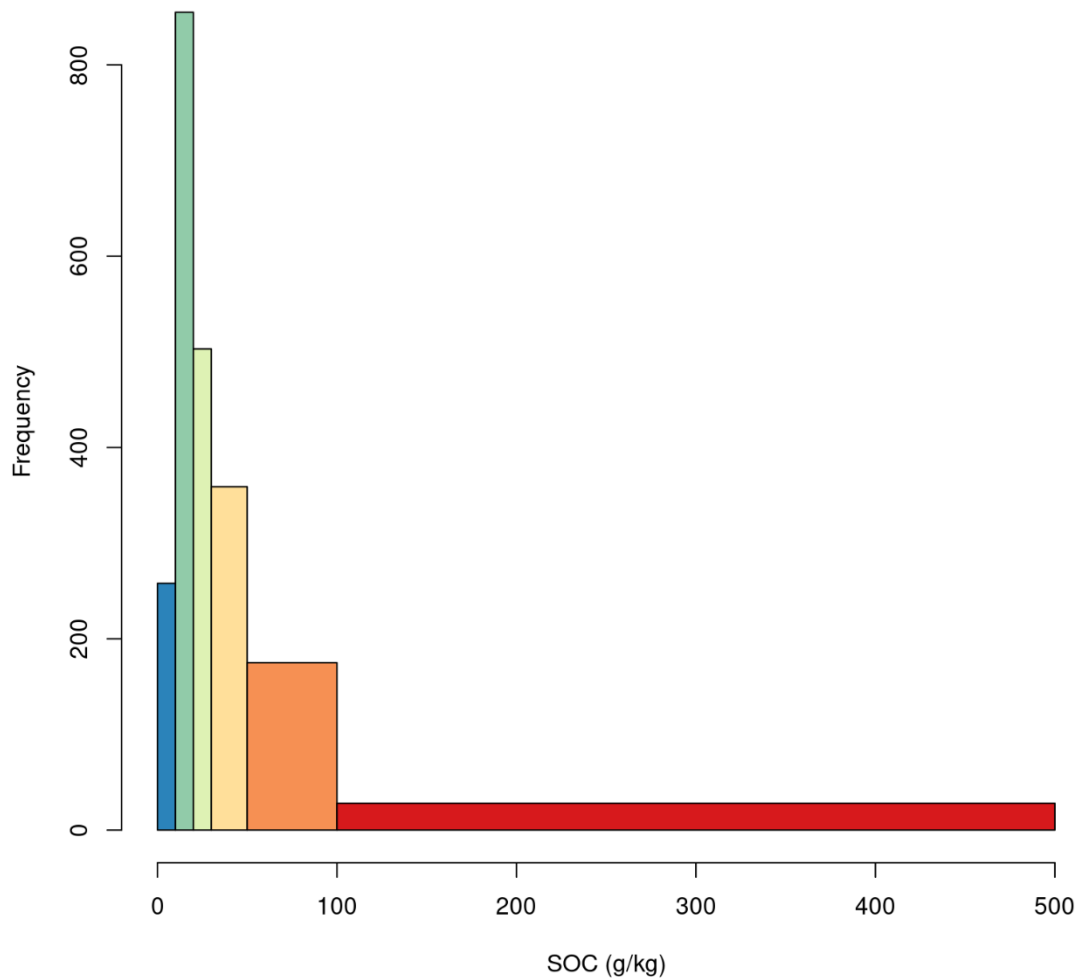


SIC g/kg

- 0 - 20
- 10 - 20
- 20 - 30
- 30 - 50
- 50 - 100
- > 100

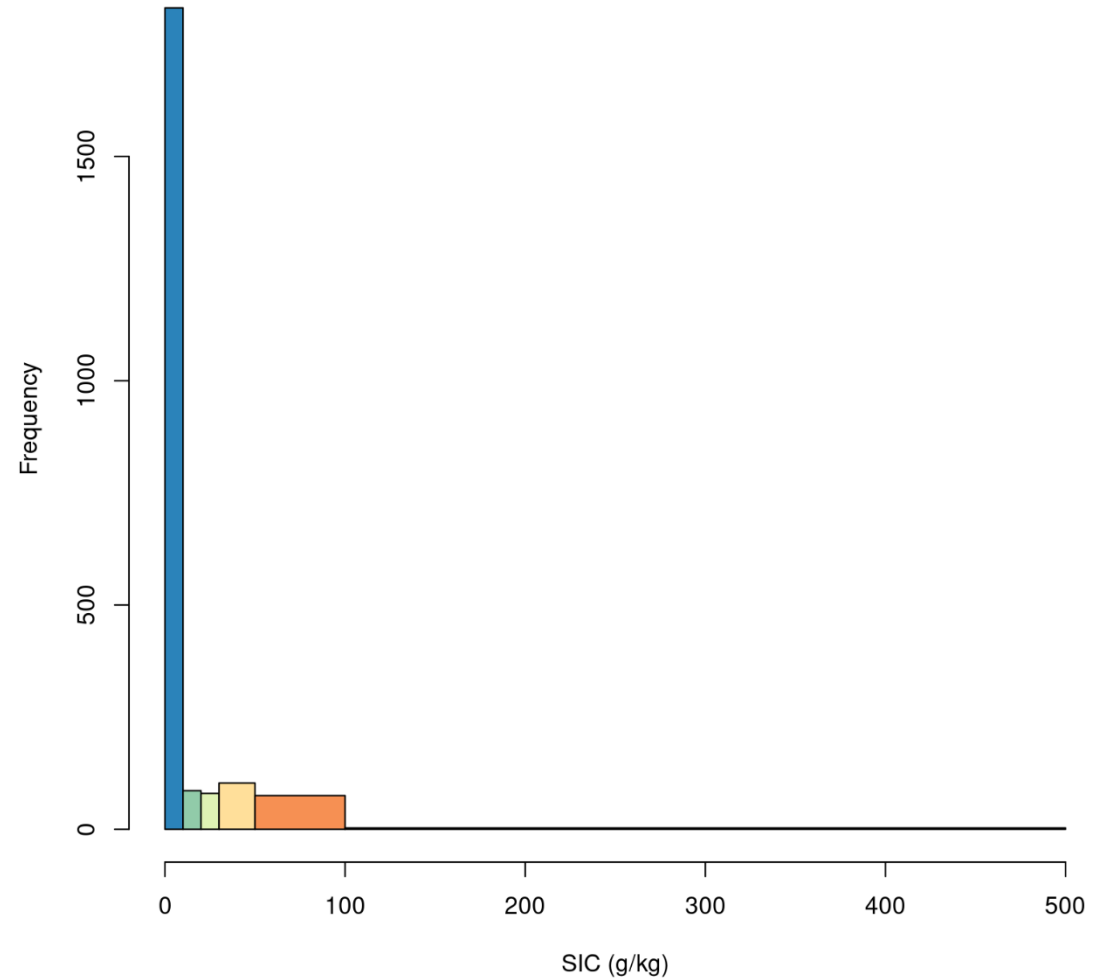
SOC

(Collected at 0-30 cm depth)



SIC

(Collected at 0-30 cm depth)



The Vis-NIR spectral measurements

Visible Near-infrared reflectance spectroscopy (LabSpec 2500, ASD)

- 350-2500 nm range
- 80 mm² area measured
- 32 co-added scans recorded as Absorbance

Soil Sample preparation:

- 0.2 mm ground
- oven-dried at 40°C



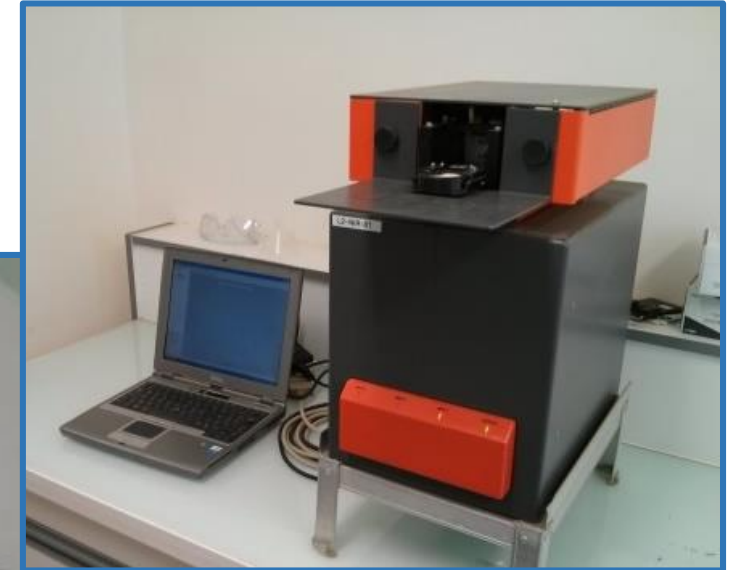
The NIR spectral measurements

Near-infrared reflectance spectroscopy (FOSS NIRSystems 5000)

- 1100-2500 nm range
- 42 mm² area measured
- 5 g subsample
- 32 co-added scans recorded as Absorbance

Soil Sample preparation:

- 0.2 mm ground
- oven-dried at 40°C

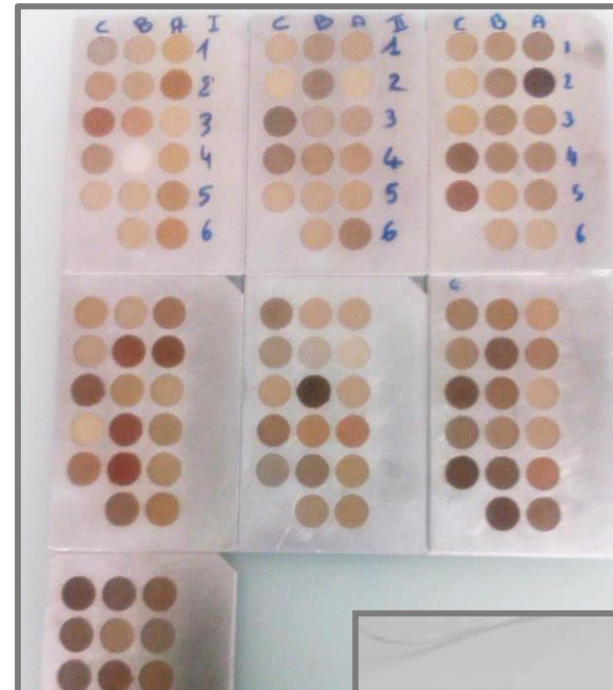


The MIR spectral measurements

Mid-infrared reflectance spectroscopy

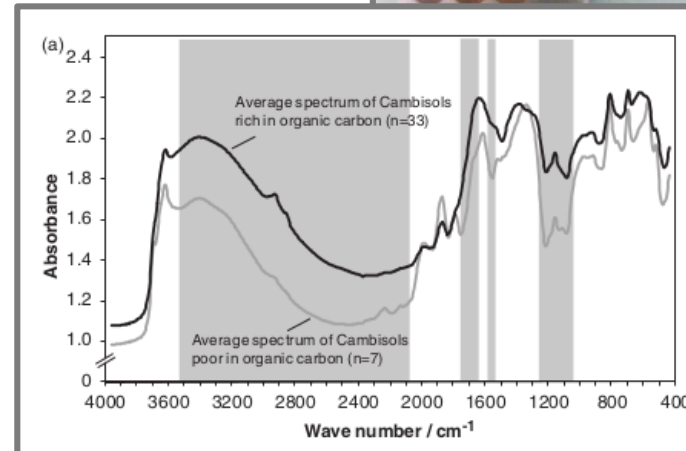
Thermo Nicolet 6700 FTIR

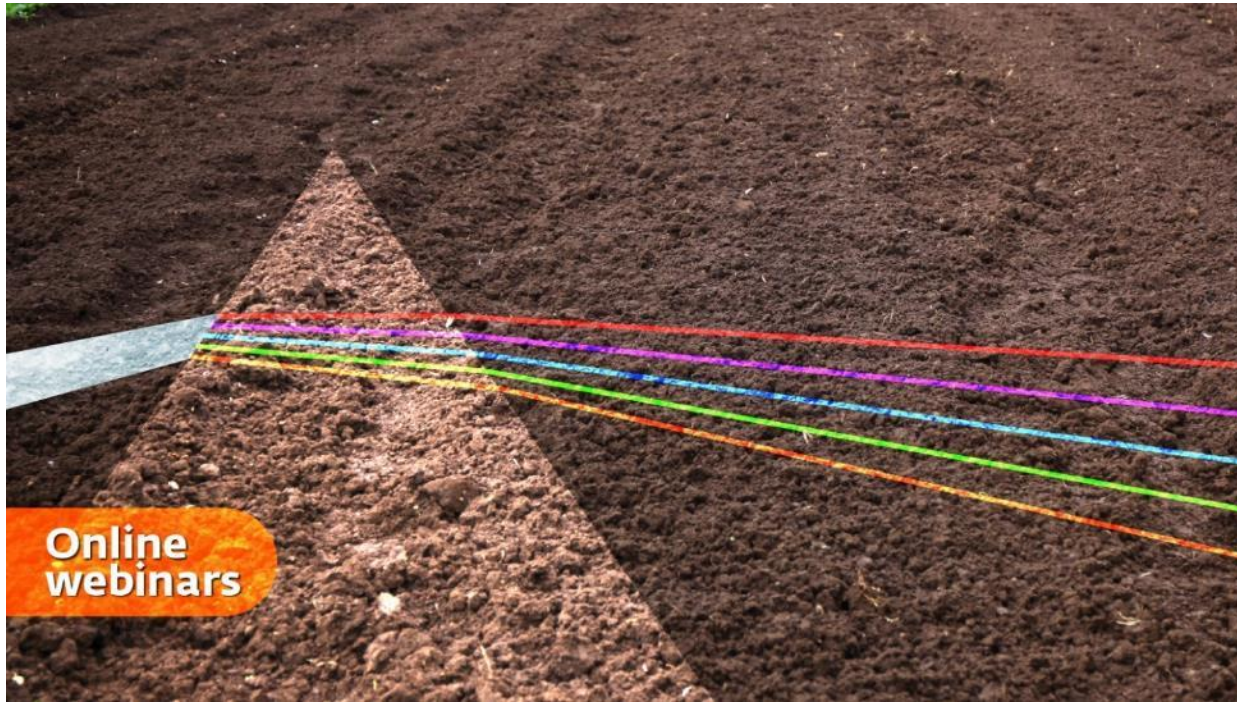
- 2500-25000 nm range
- 13 mm² area measured
- 0.5 g subsample
- 32 co-added scans recorded as Absorbance



Soil Sample preparation:

- 0.2 mm ground
- oven-dried at 40°C






Can we use the French spectral library for soil properties estimation *at National Scale (in French Territory)?*

Can we use the French spectral library for soil properties estimation *at National Scale (in French territory)?*

=> Scenario 1

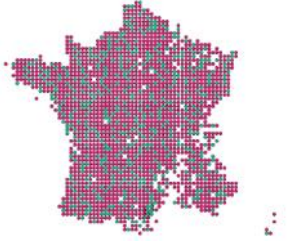
1 st scenario	
Area coverage	Calib DB = Test DB
Database sizes	Calib DB > Test DB
	

Questions

- Which wavelength range performs the best? NIR, MIR?
- What is the optimum number of Calibration samples?
- How to select Calibration data?



Clairotte et al., 2016. Geoderma



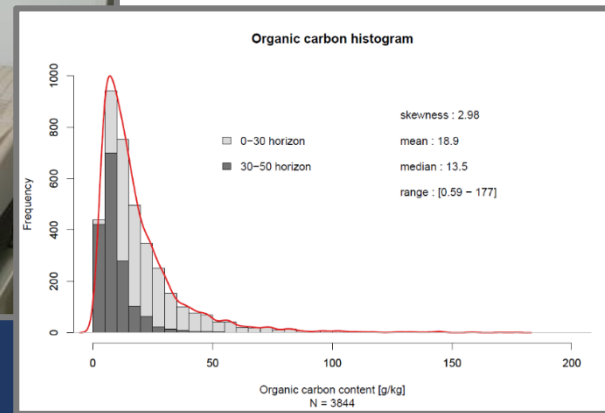
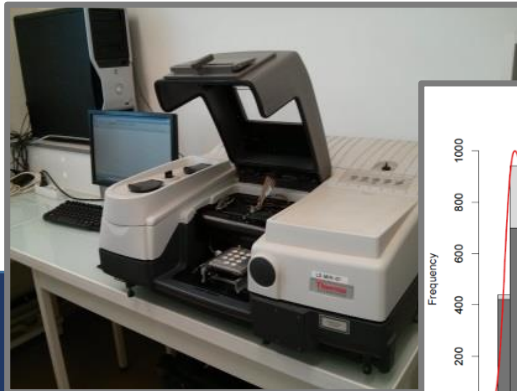
Clairotte et al., 2016. *Geoderma*

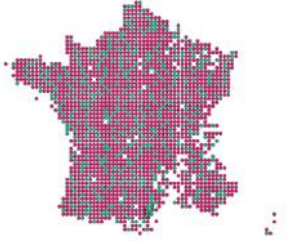
Questions

- Which wavelength range performs the best? NIR, MIR?
- What is the optimum number of Calibration samples?
- How to select Calibration data?

Data

- ✓ ~3800 Soil samples of RMQS
Collected at 0-30 cm and 30-50 cm depth
- ✓ NIR and MIRS spectra
- ✓ Soil Organic Carbon (SOC)





Clairotte et al., 2016. Geoderma

Questions

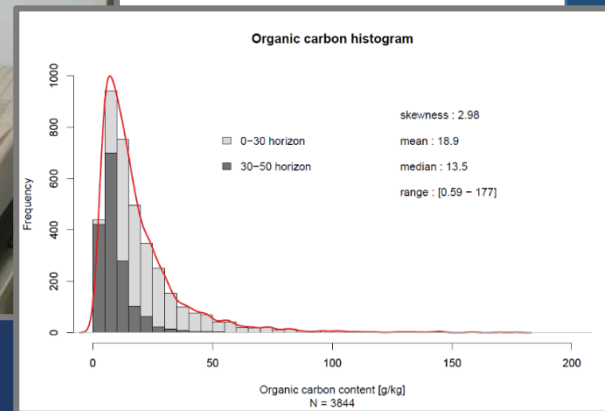
- Which wavelength range performs the best? NIR, MIR?
- What is the optimum number of Calibration samples?
- How to select Calibration data?

Methods

- ✓ PLSR to build regression models
- ✓ 10 % of samples (= 380) used for Independent Validation
- ✓ 10 % of samples (= 380) used for model tuning
- ✓ Calibration Data selected among remaining samples (~3040 samples):
 - randomly (with 10 replicates)
 - by Kennard-Stone algorithm (with 10 replicates)
 - By spectral neighbours
- ✓ $N_{cal} = 20 - 100\%$ of the remaining samples (~3040 samples)

Data

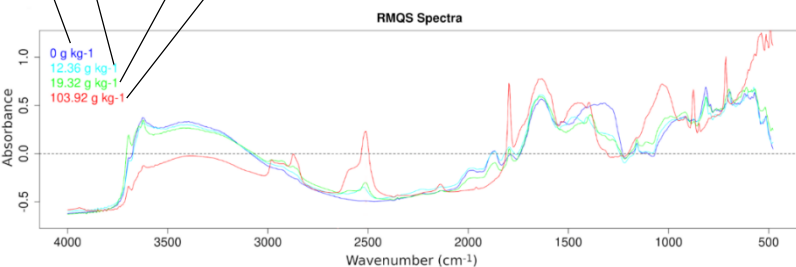
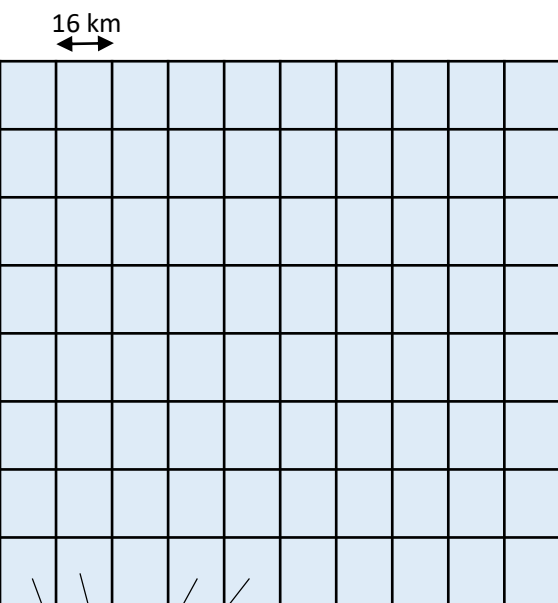
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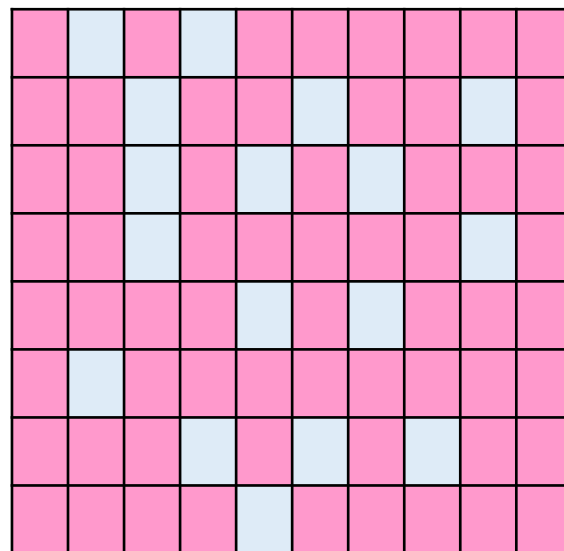


3 ways for the Calibration Data selection

RMQS dataset

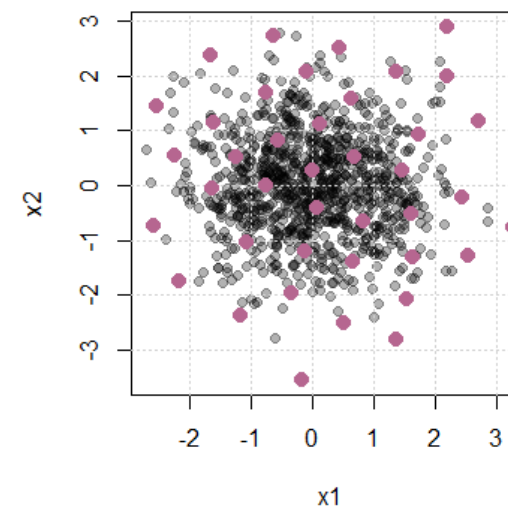


Random selection



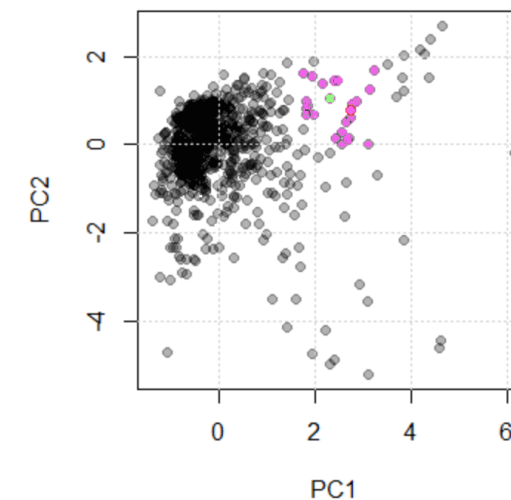
Kennard-Stone

Based on spectral representativeness
(Kennard and Stone, 1969)



Local calibration samples

Based on Spectral neighbours
(Shenk et al., 1997)

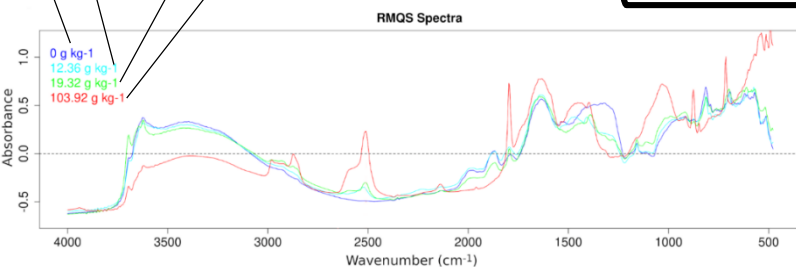
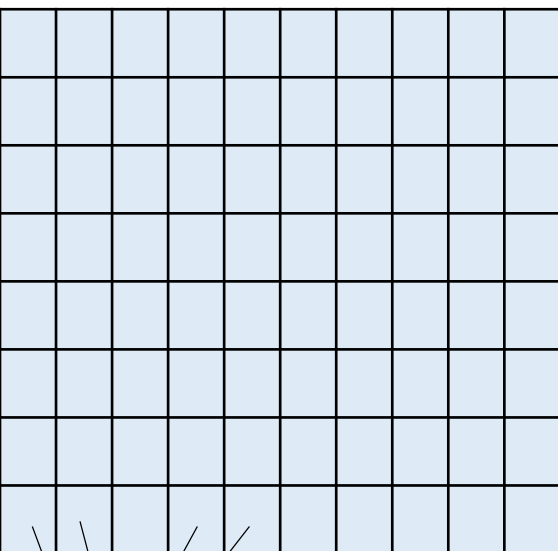




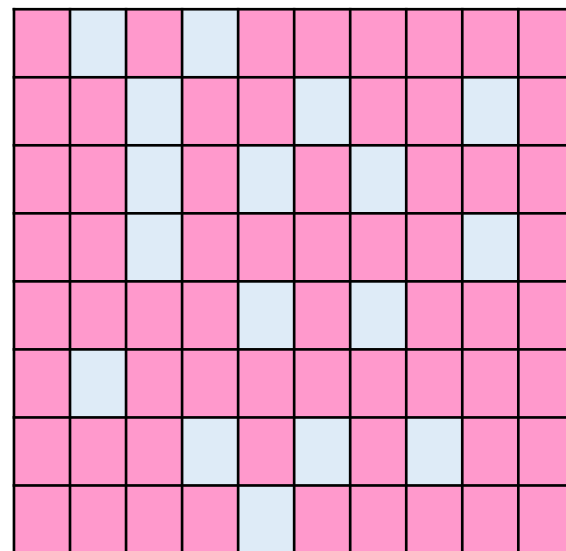
3 ways for the Calibration Data selection

RMQS dataset

16 km

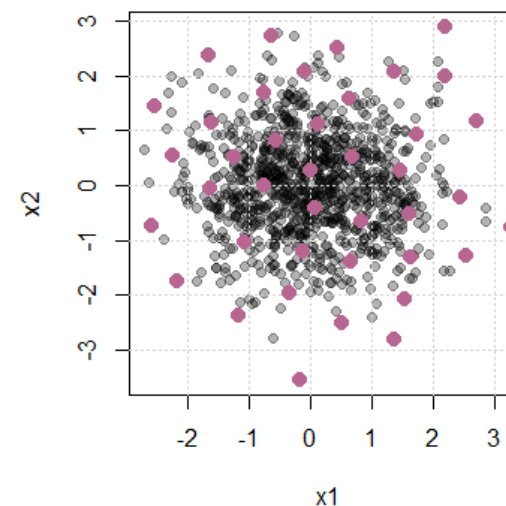


Random selection



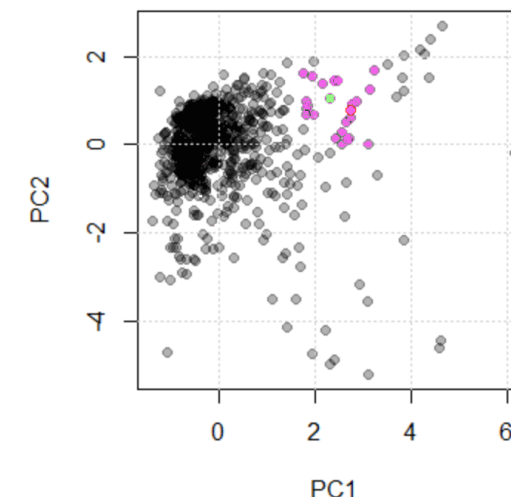
Kennard-Stone

Based on spectral representativeness
(Kennard and Stone, 1969)



Local calibration samples

Based on Spectral neighbours
(Shenk et al., 1997)



Global PLSR

Local PLSR

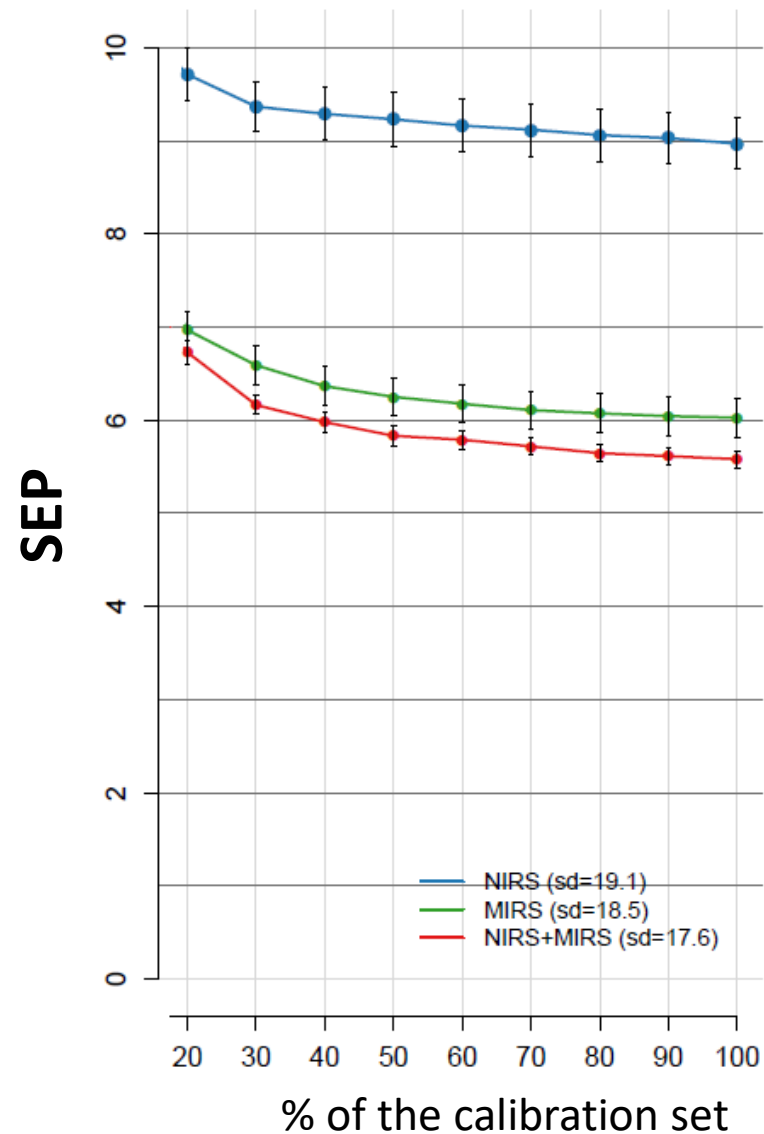
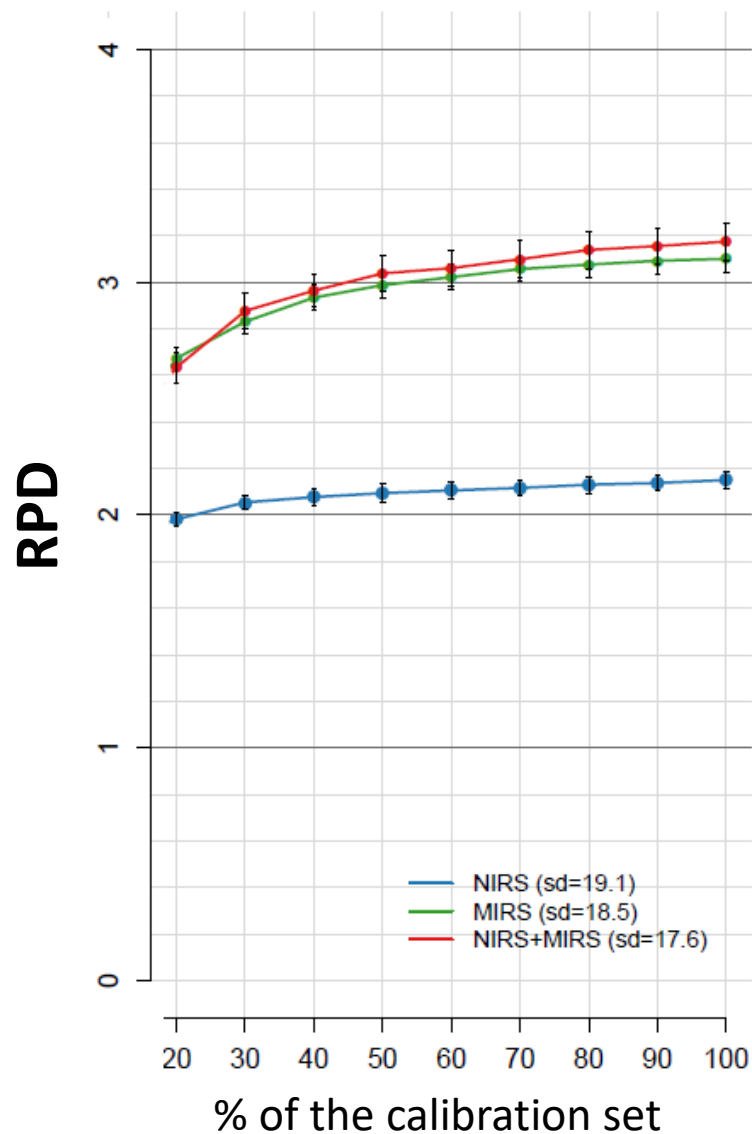


Three strategies for Calibration set Selection

Soil Organic Carbon (g kg⁻¹)

— Random selection

VAL.set (380)





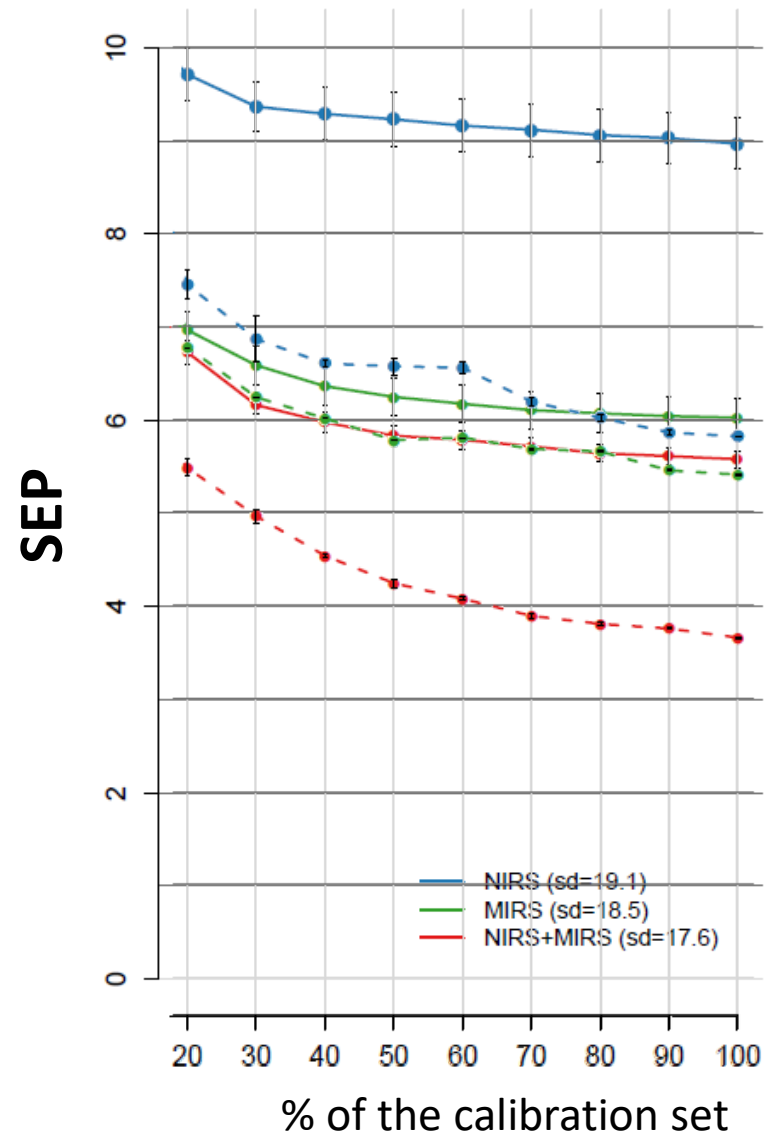
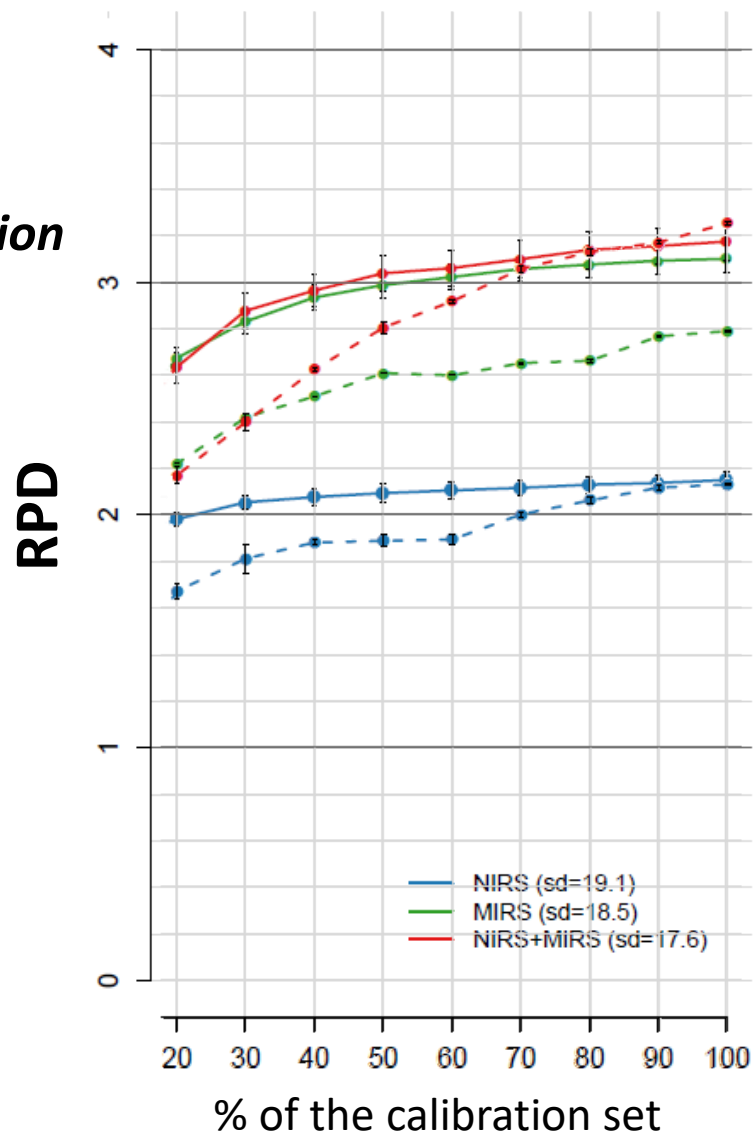
Three strategies for Calibration set Selection

Soil Organic Carbon (g kg⁻¹)

— Random selection

---- Kennard-Stone selection

VAL.set (380)



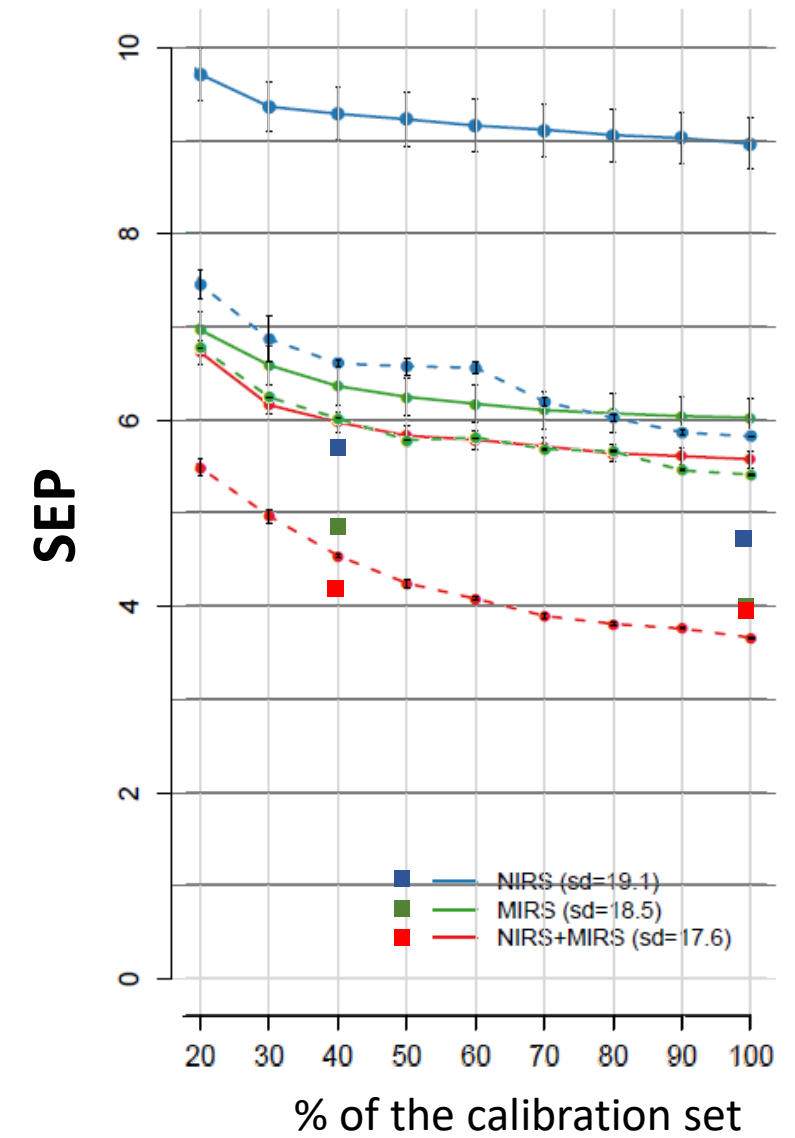
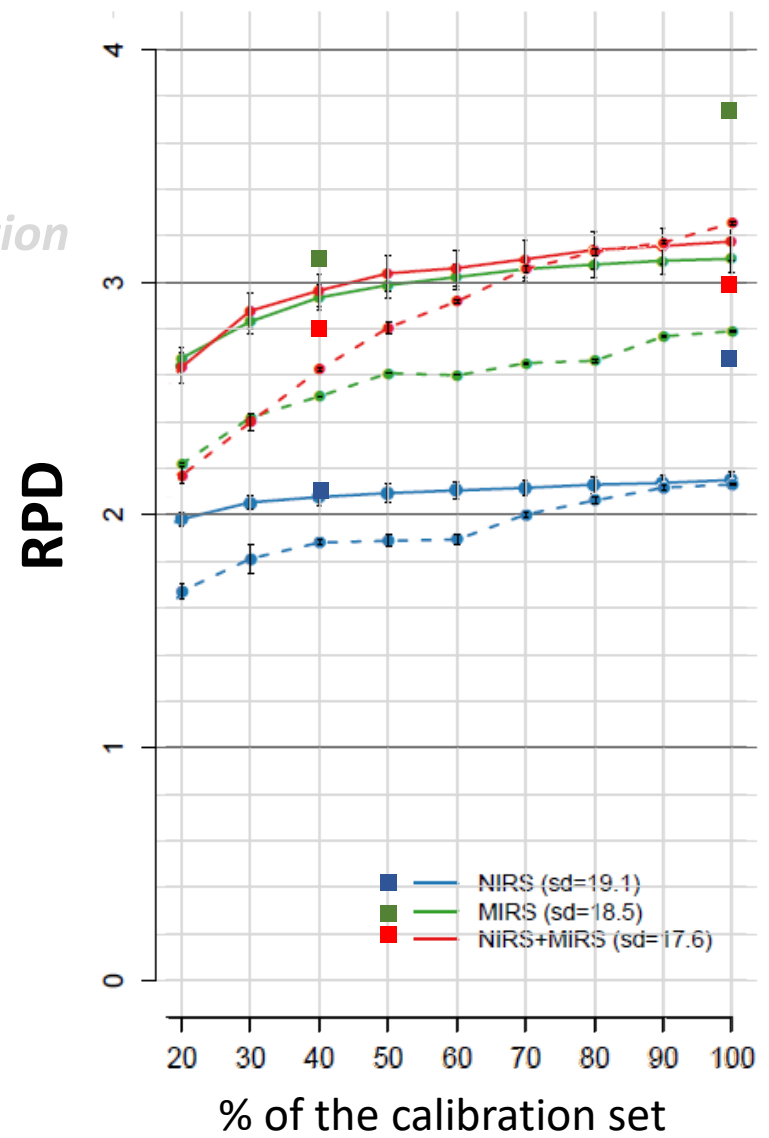


Three strategies for Calibration set Selection

Soil Organic Carbon (g kg⁻¹)

- Random selection
- Kennard-Stone selection
- Local Calibration

VAL.set (380)



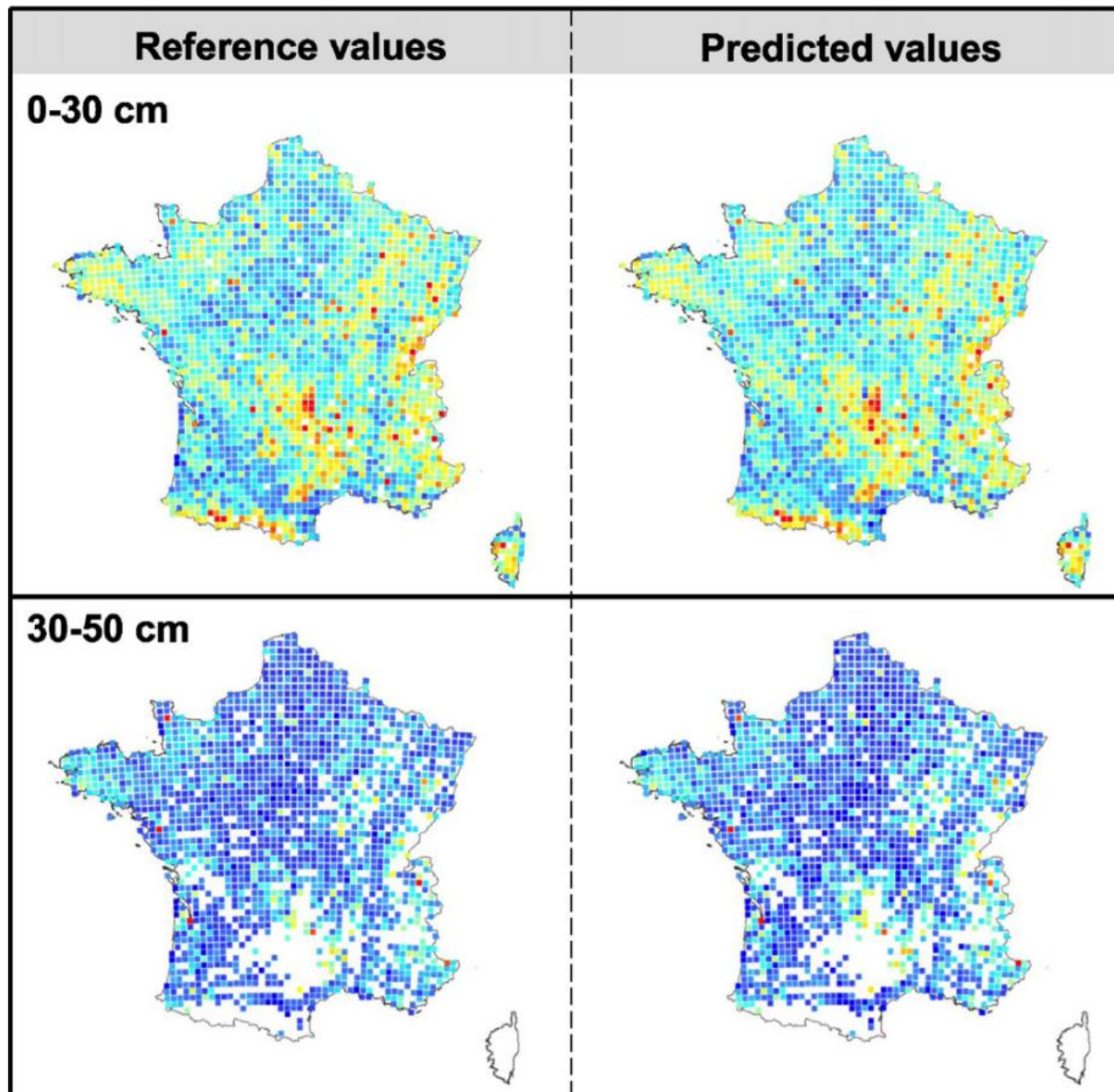


MIRS

Local PLSR

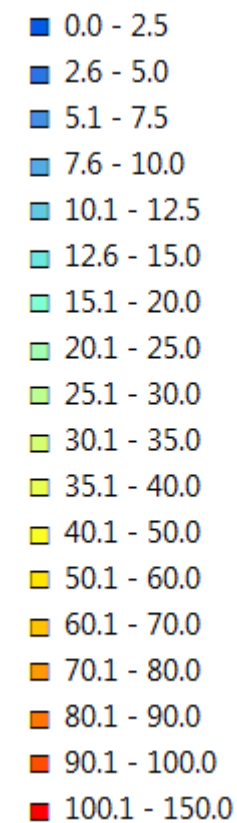
Calibration set = 100 %
= 3076 samples

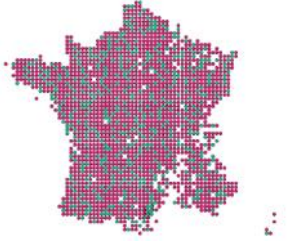
Validation set = 380 samples



SEP = 4.7 g/kg

Soil Organic Carbon (g kg^{-1})





Clairotte et al., 2016. Geoderma

Questions

- Which wavelength range performs the best? NIR, MIR?
- What is the optimum number of Calibration samples?
- How to select Calibration data?

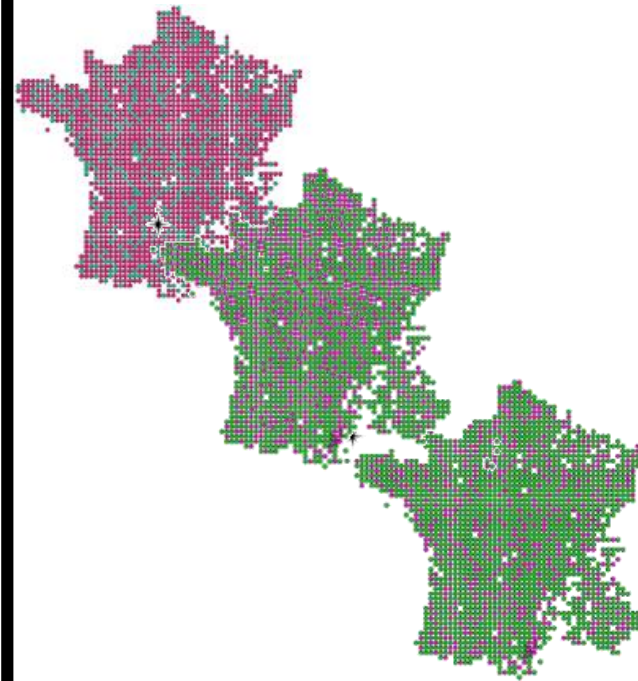
Highlights

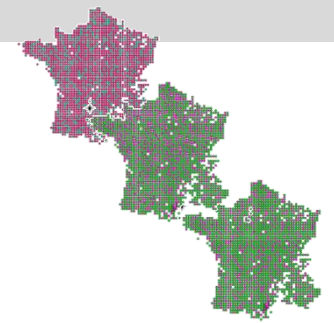
- ❖ MIR >> NIR for SOC prediction at our National scale.
- ❖ The greater the number of samples, the better the performance.
- ❖ Even 20% of the National Dataset provided correct accuracy of SOC estimation.
- ❖ Spectral neighbours >> Kennard-Stone >> Random
- ❖ Maps of predicted properties appropriate for large-scale soil inventories and mapping studies, but not for accurate carbon monitoring

Can we use the French spectral library for soil properties estimation *at National Scale (in French territory)?*

=> Scenario 2

	1 st scenario	2 nd scenario
Area coverage	Calib DB = Test DB	Calib DB = Test DB
Database sizes	Calib DB > Test DB	Nb Calib DB = 100% - Nb Valid DB

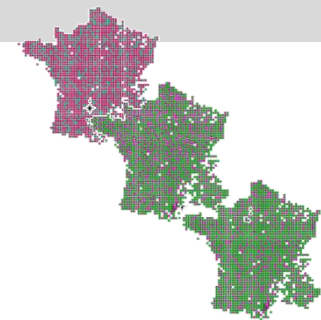




Grinand et al., 2012. EJSS

Question

- Which performances can we expect depending on the number of Calibration samples (from higher to lower than the number of Validation samples)?



Grinand et al., 2012. EJSS

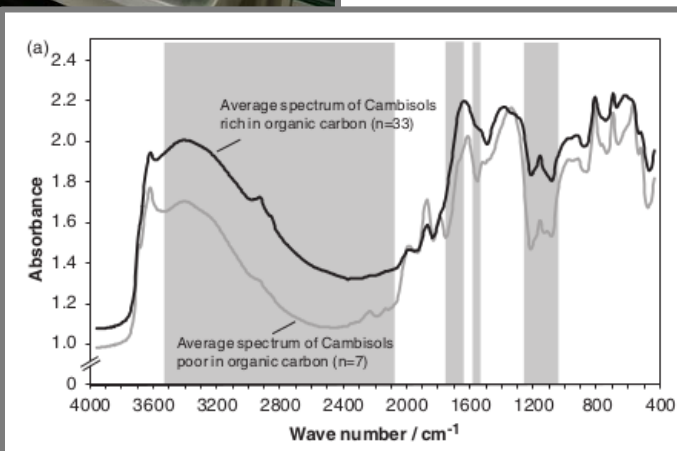
Question

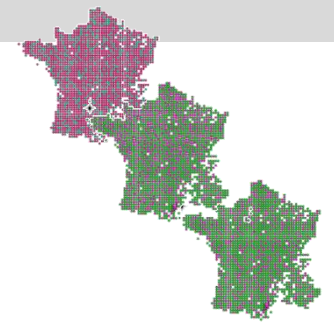
- Which performances can we expect depending on the number of Calibration samples (from higher to lower than the number of Validation samples)?



Data

- ✓ 2086 soil samples of RMQS Collected at 0-30 cm depth
- ✓ MIR spectra
- ✓ Soil Organic Carbon (SOC) and Soil Inorganic Carbon (SIC)





Grinand et al., 2012. EJSS

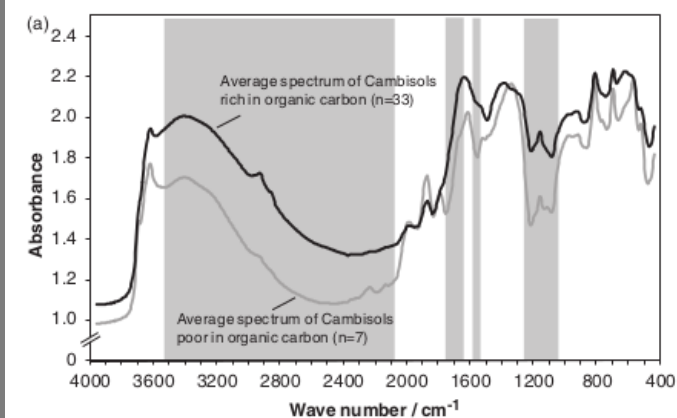
Question

- Which performances can we expect depending on the number of Calibration samples (from higher to lower than the number of Validation samples)?



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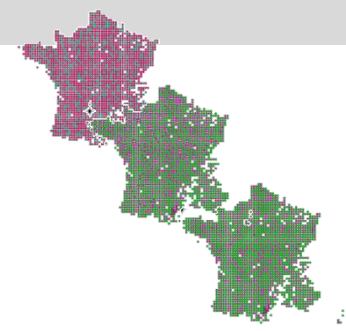
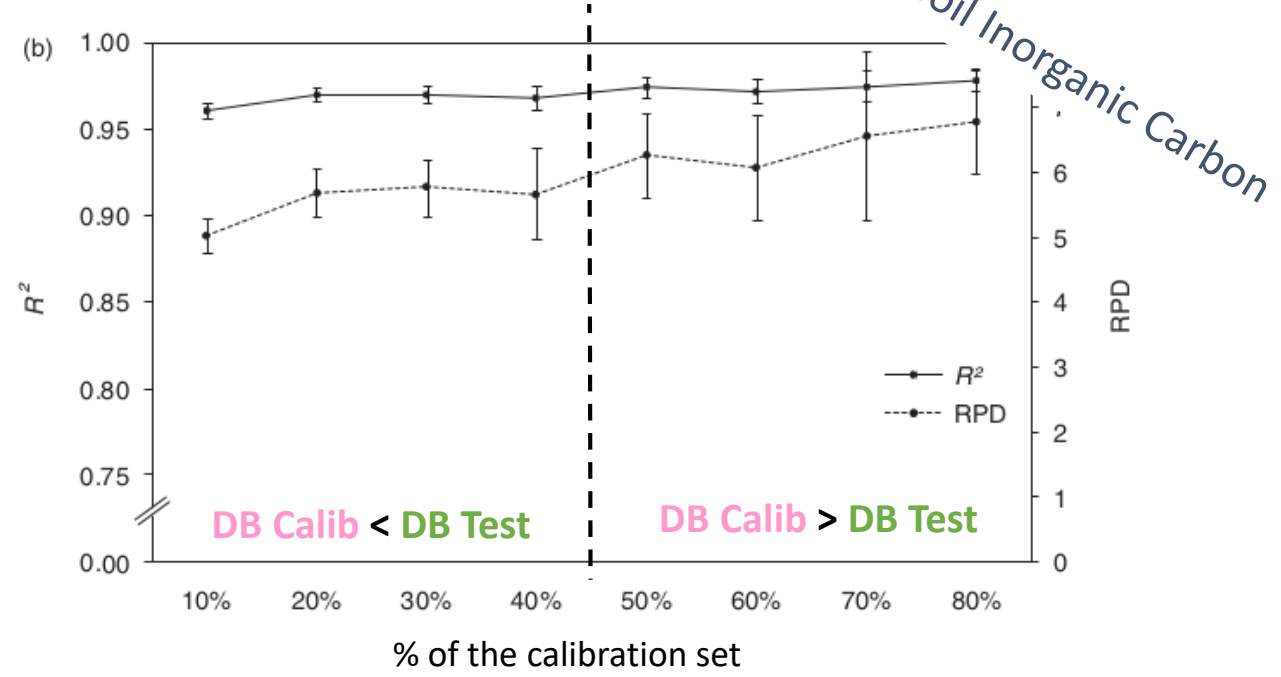
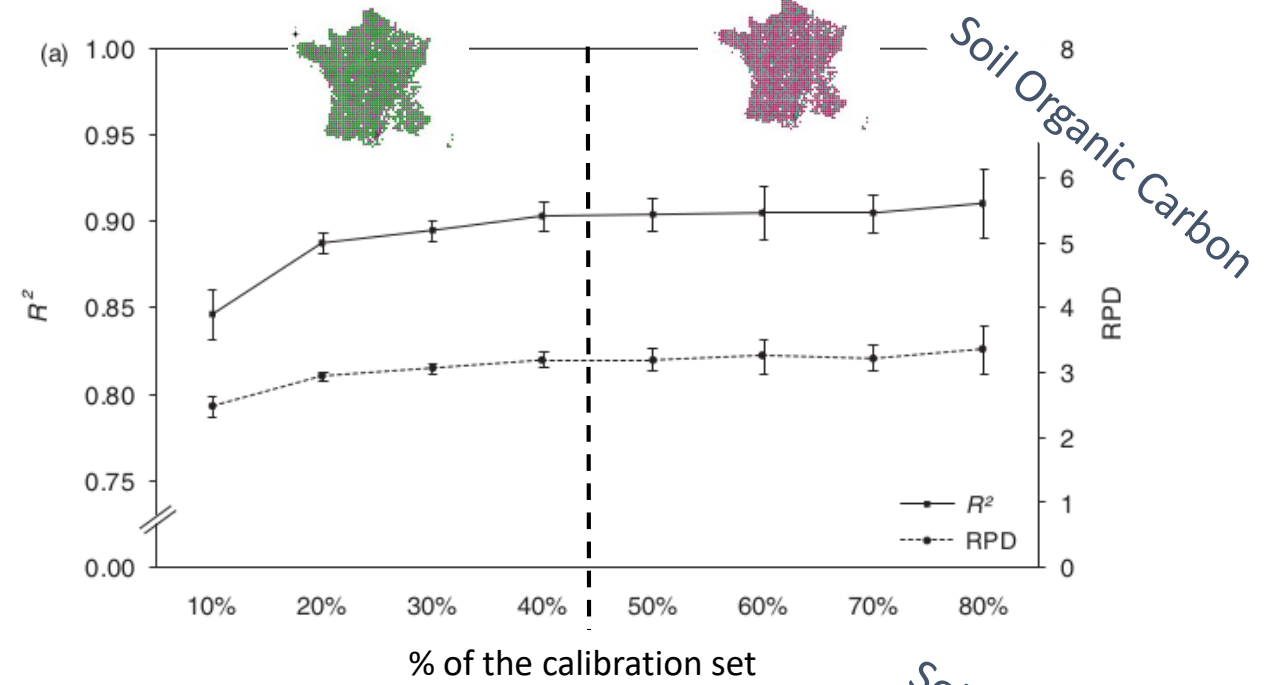
Methods

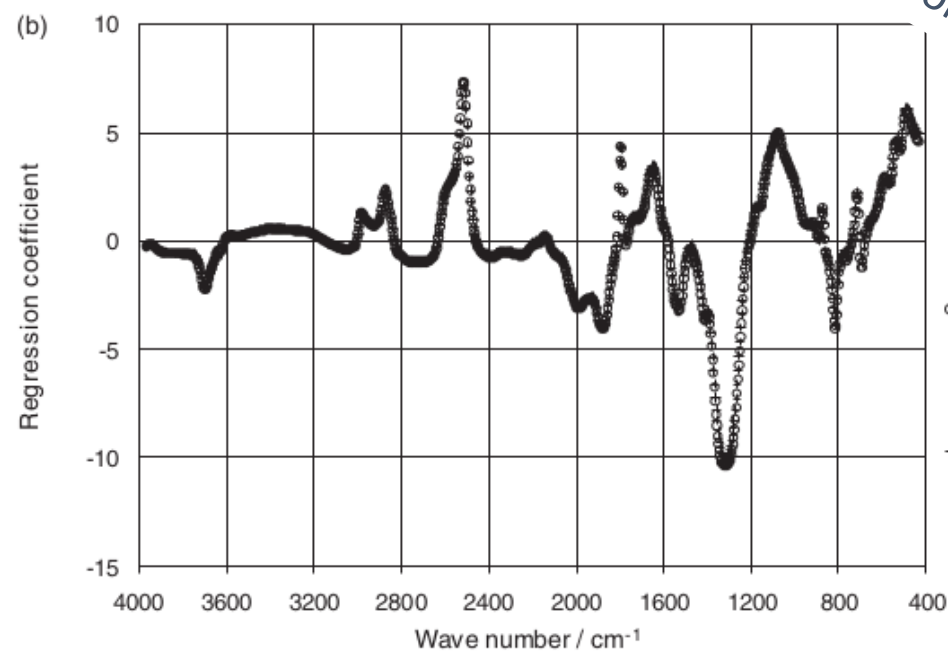
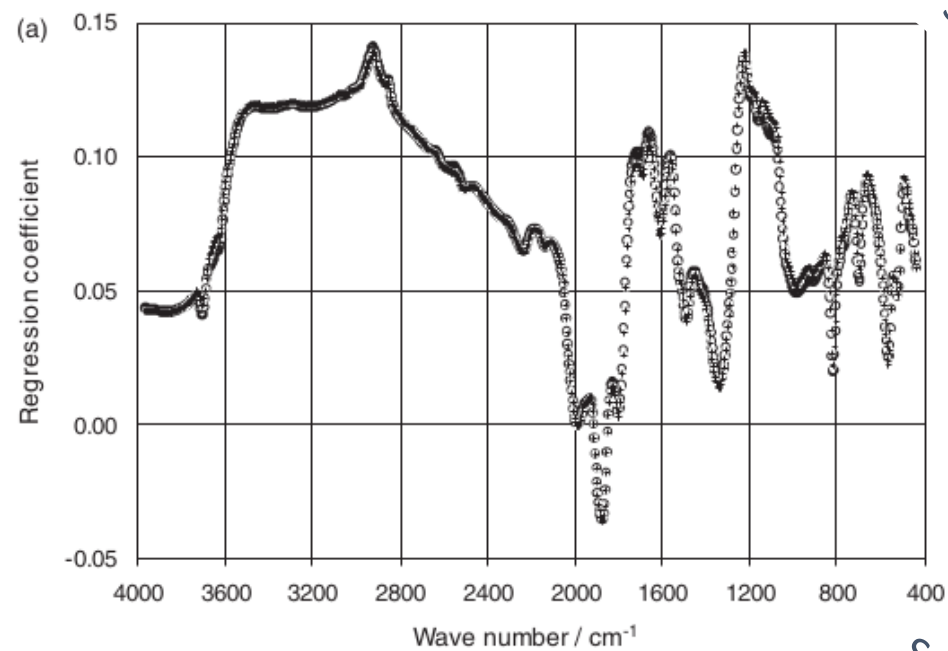
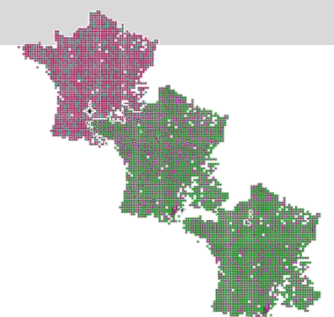
- ✓ PLSR to build regression models
- ✓ Calibration using $N_{cal} = 10-80\%$ of the set
- ✓ Five random selection of samples
- ✓ Validation using remaining samples ($100\% - N_{cal}$)

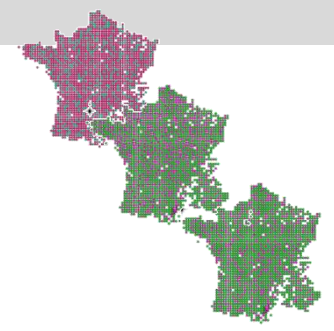
Random selection of Calibration set

CAL.set (X %)

VAL.set (100 -X %)







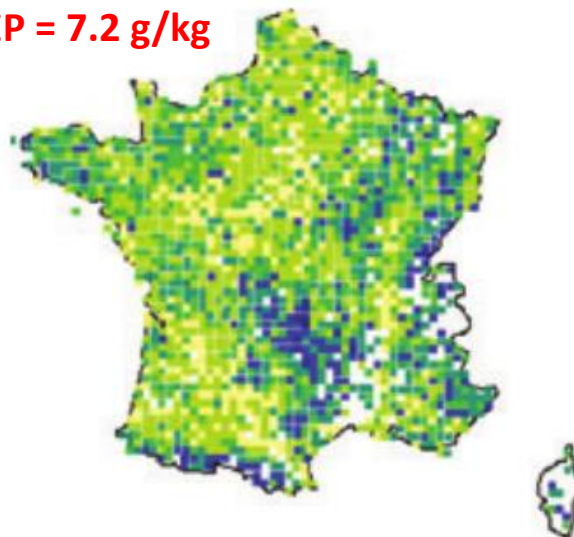
**Random selection of
Calibration set**

CAL.set (20 %)

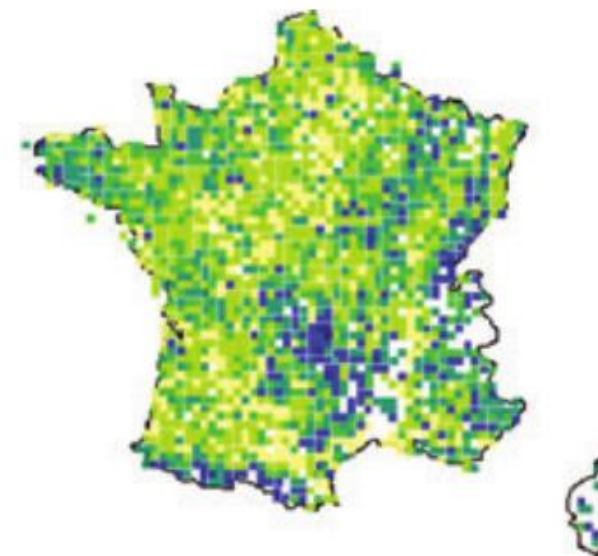
VAL.set (80 %)

(a) Predicted
organic carbon

SEP = 7.2 g/kg

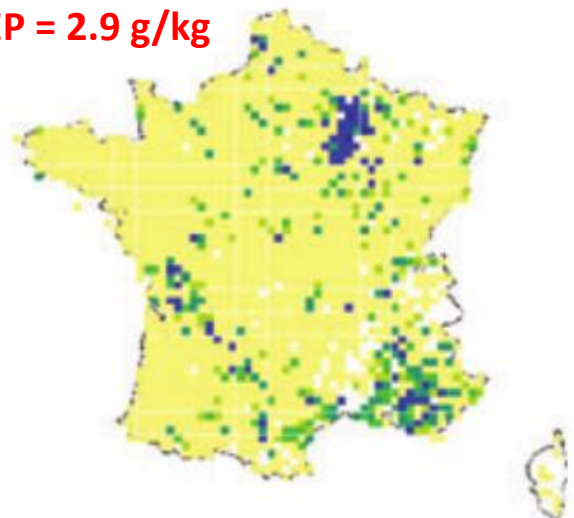


(b) Measured
organic carbon

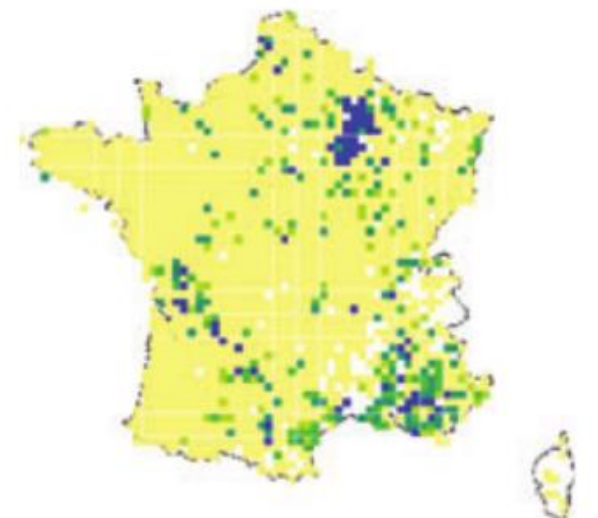


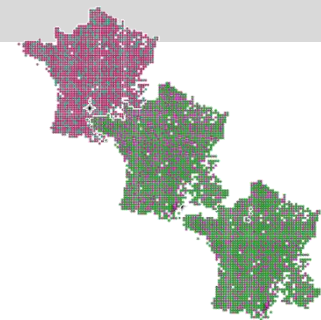
(c) Predicted
inorganic carbon

SEP = 2.9 g/kg



(d) Measured
inorganic carbon





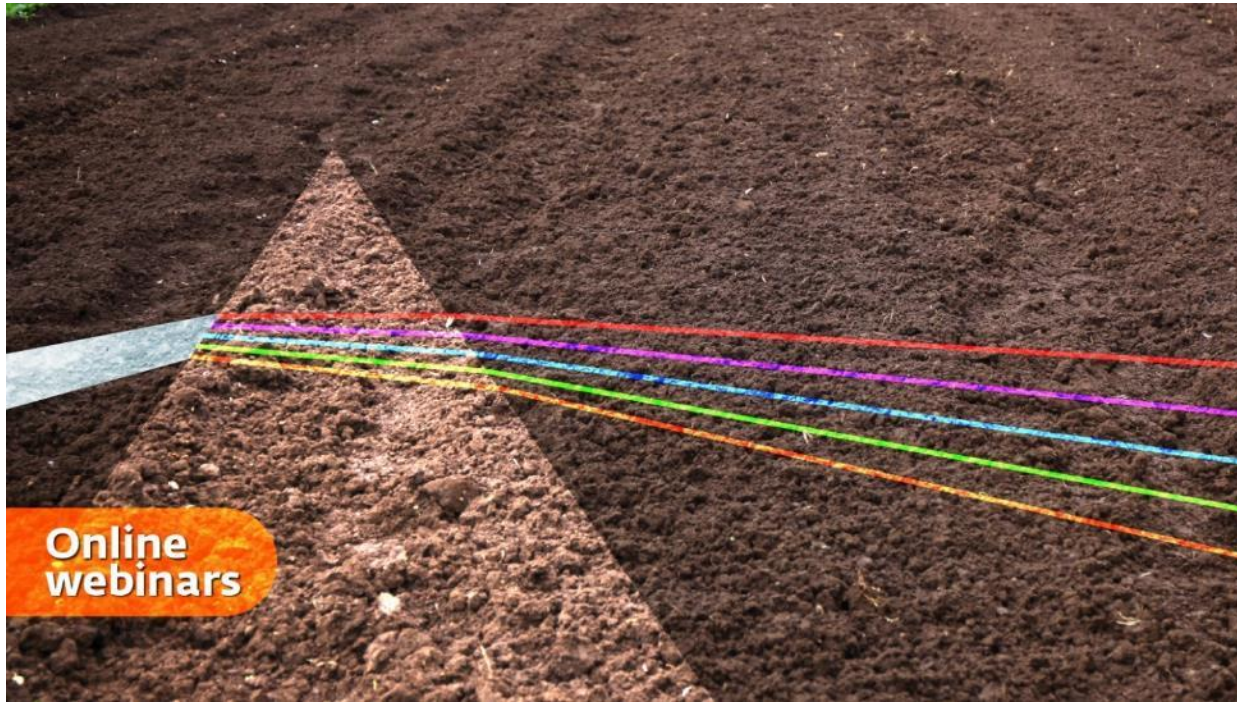
Grinand et al., 2012. EJSS

Question

- Which performances can we expect depending on the number of Calibration samples (from higher to lower than the number of Validation samples)?

Highlights

- ❖ Optimal calibrations were achieved by using 20% of the RMQS dataset for both SOC and SIC predictions....
 - With a similarity between regression coefficients of calibration equations that used 20 and 100% of the total set
- ❖ Maps of predicted properties still appropriate for large-scale soil inventories and mapping studies, but not for accurate carbon monitoring

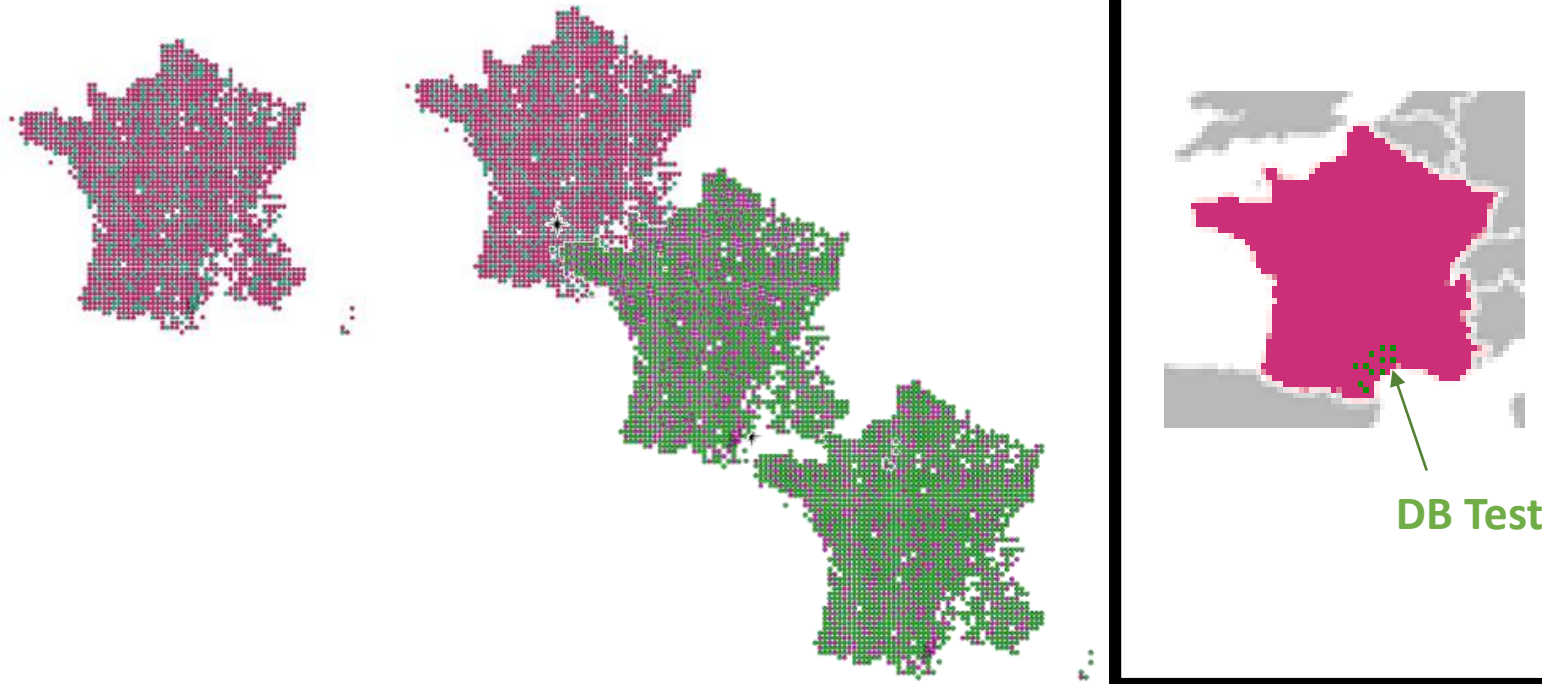


Can we use the French spectral library for soil properties estimation *at Regional Scale (in France)?*

Can we use the French spectral library for soil properties estimation *at Regional Scale (in French territory)?*

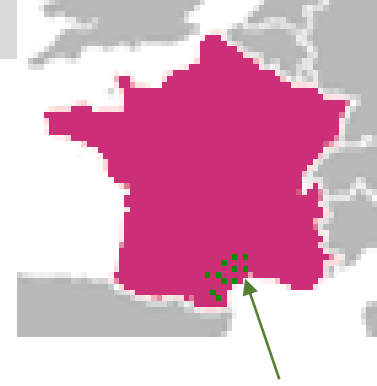
=> Scenario 3

	1 st scenario	2 nd scenario	3 rd scenario
Area coverage	Calib DB = Test DB	Calib DB = Test DB	Test DB \in Calib DB
Database sizes	Calib DB > Test DB	Nb Calib DB = 100% - Nb Calib DB	Calib DB \gg Test DB



Questions

- Which performances can we expect when the validation samples come from a region compared to Calibration samples coming from National area?
- Which approach is appropriate in this specific situation?

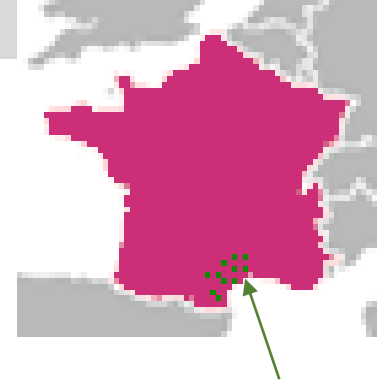


DB Test

Barthes et al., 2020. Geoderma

Questions

- Which performances can we expect when the validation samples come from a region compared to Calibration samples coming from National area?
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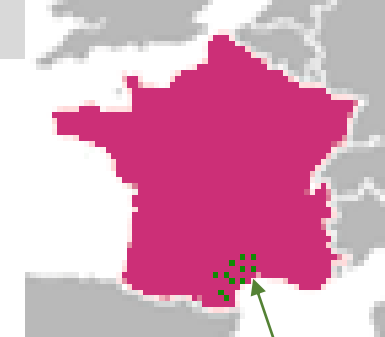
DB Test

Barthes et al., 2020. Geoderma

Data

- ✓ 2178 soil samples of RMQS
Collected at 0-30 cm depth
- ✓ 164 regional soil samples from
Vineyard plots (South of France)
 - A sample per vineyard plot
 - Collected at 0-15 cm depth
- ✓ MIRS spectra
- ✓ Soil Inorganic Carbon (SIC)





DB Test

Questions

- Which performances can we expect when the validation samples come from a region compared to Calibration samples coming from National area?
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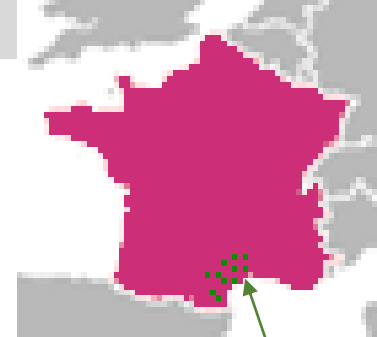
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- ✓ Soil Inorganic Carbon (SIC)



Methods

- ✓ PLSR to build regression models
- ✓ Four tested approaches. Calibration from
 1. 2178 soil samples of RMQS
 2. 2178 soil samples of RMQS + spiked Regional samples
 3. spectral neighbours of RMQS
 4. spectral neighbours of RMQS + spiked Regional samples
- ✓ Validation using 134 among the 164 regional samples
- ✓ 30 remaining samples possibly used for spiking



DB Test

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- Which performances can we expect when the validation samples come from a region compared to Calibration samples coming from National area?
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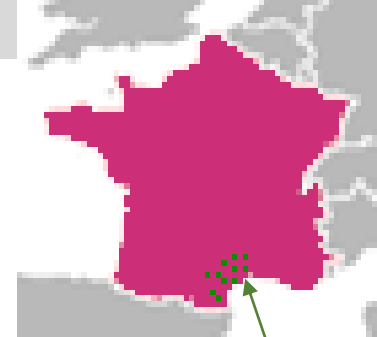
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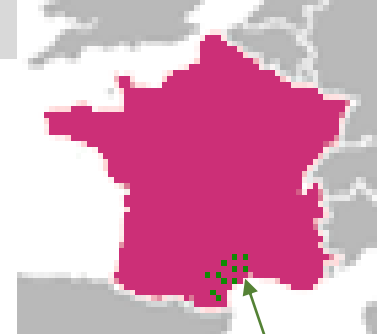
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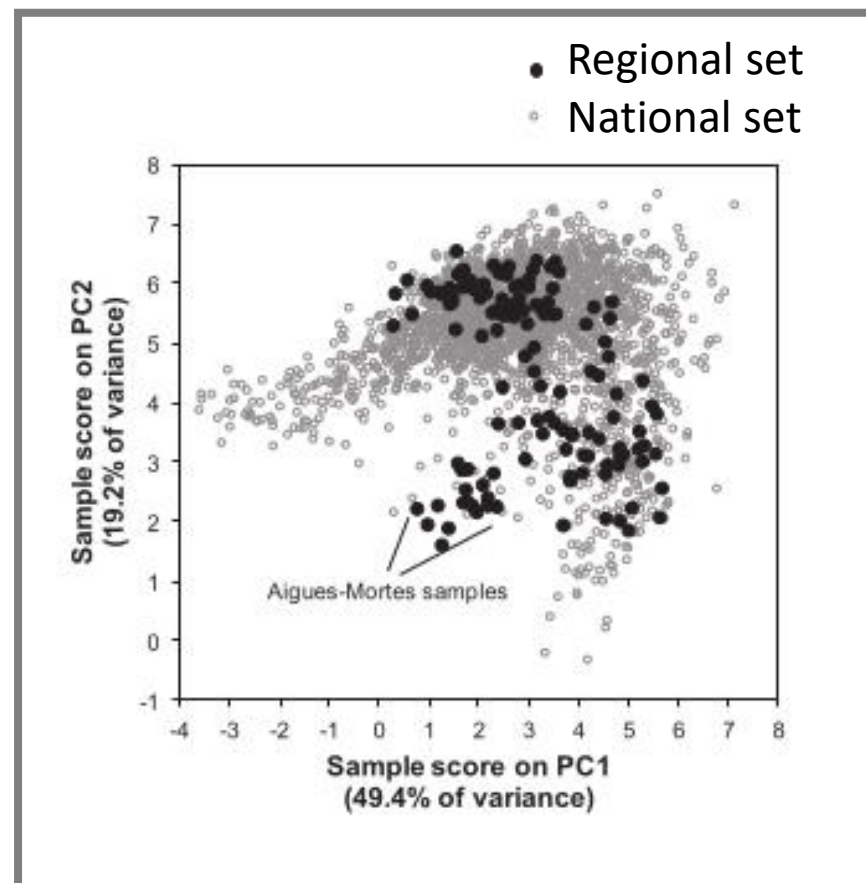
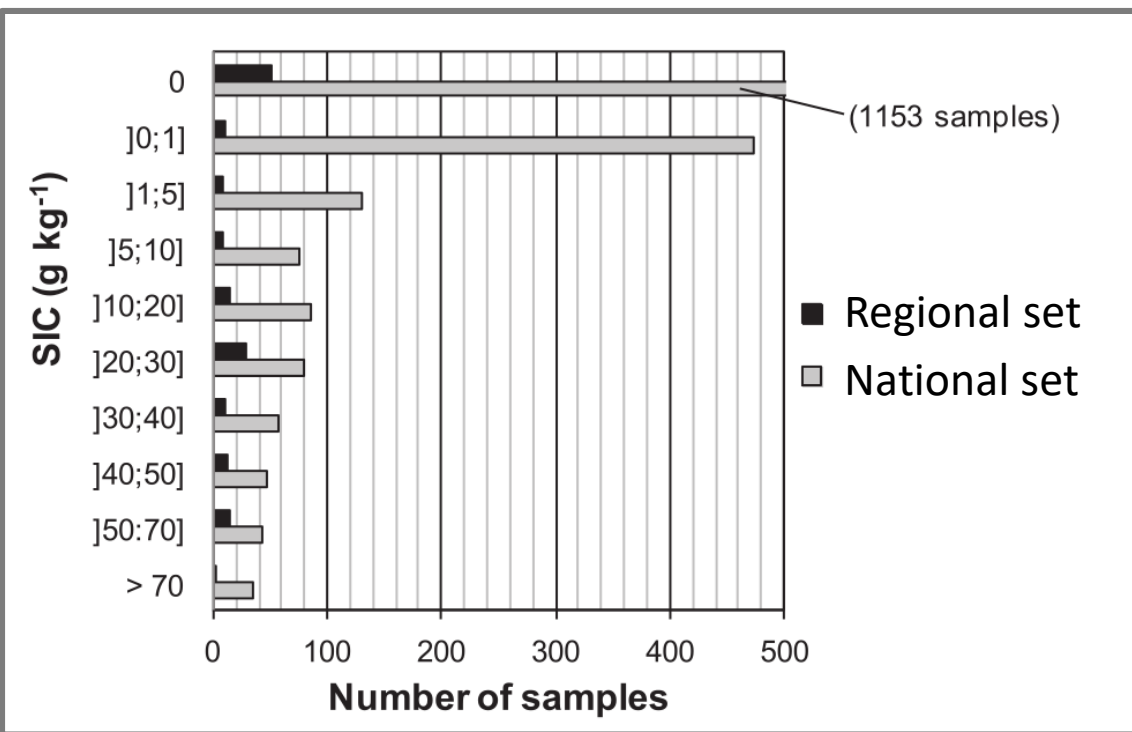


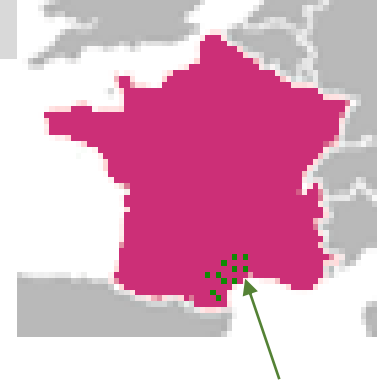
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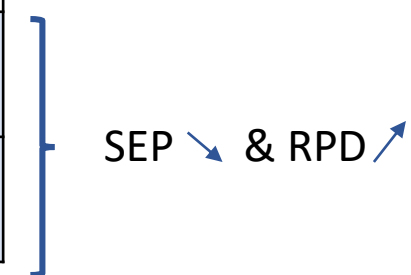
DB Test

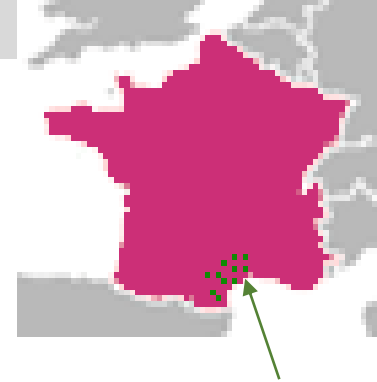




DB Test

	N_{cal} from RMQS	N_{spike}	N_{val}	SEP_{val}	R^2_{val}	RPD_{val}
Global Models for SIC predictions	2178	0	134	5.2	0.96	3.7
	2178	10	134	4.9	0.96	3.9

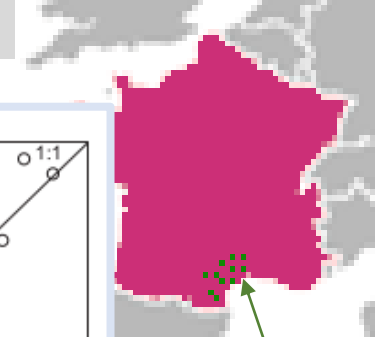




DB Test

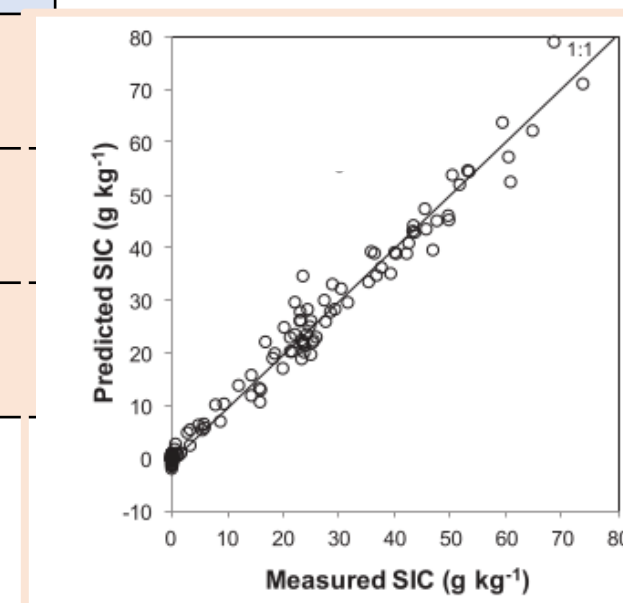
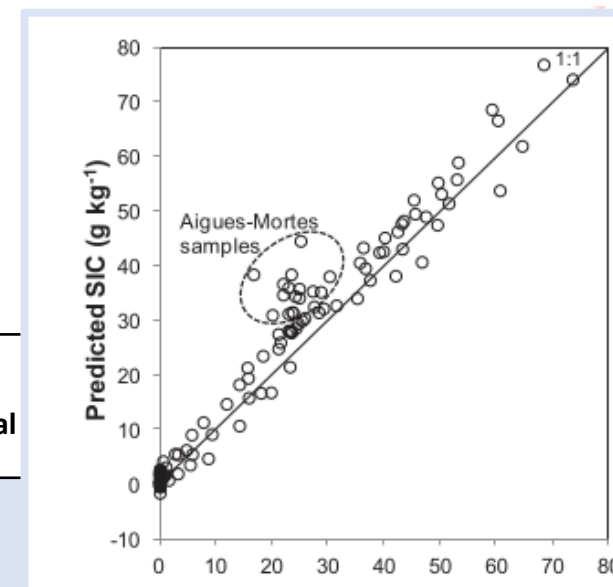
	N_{cal} from RMQS	N_{spike}	N_{val}	SEP_{val}	R²_{val}	RPD_{val}
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	2178	10	134	4.9	0.96	3.9
Local Models for SIC predictions	From 4 to 2178	0	133	4.8	0.95	4.1
	From 4 to 2178	10	134	2.7	0.98	7.3
	From 50 to 2178	10	115	2.3	0.99	8.9

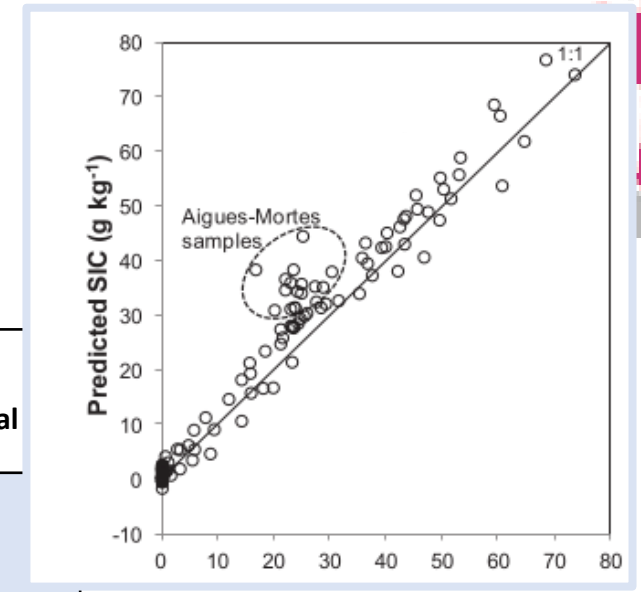
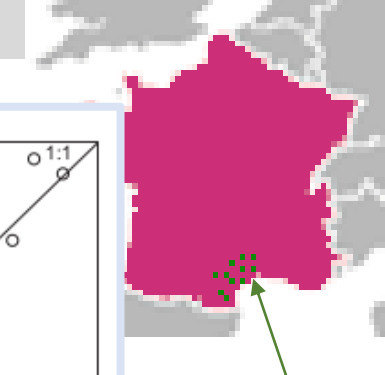




DB Test

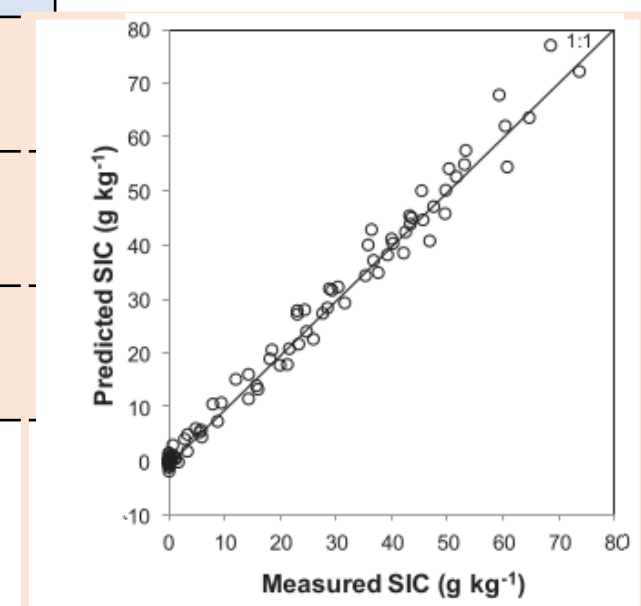
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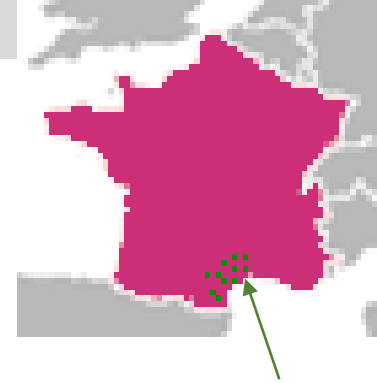




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DB Test

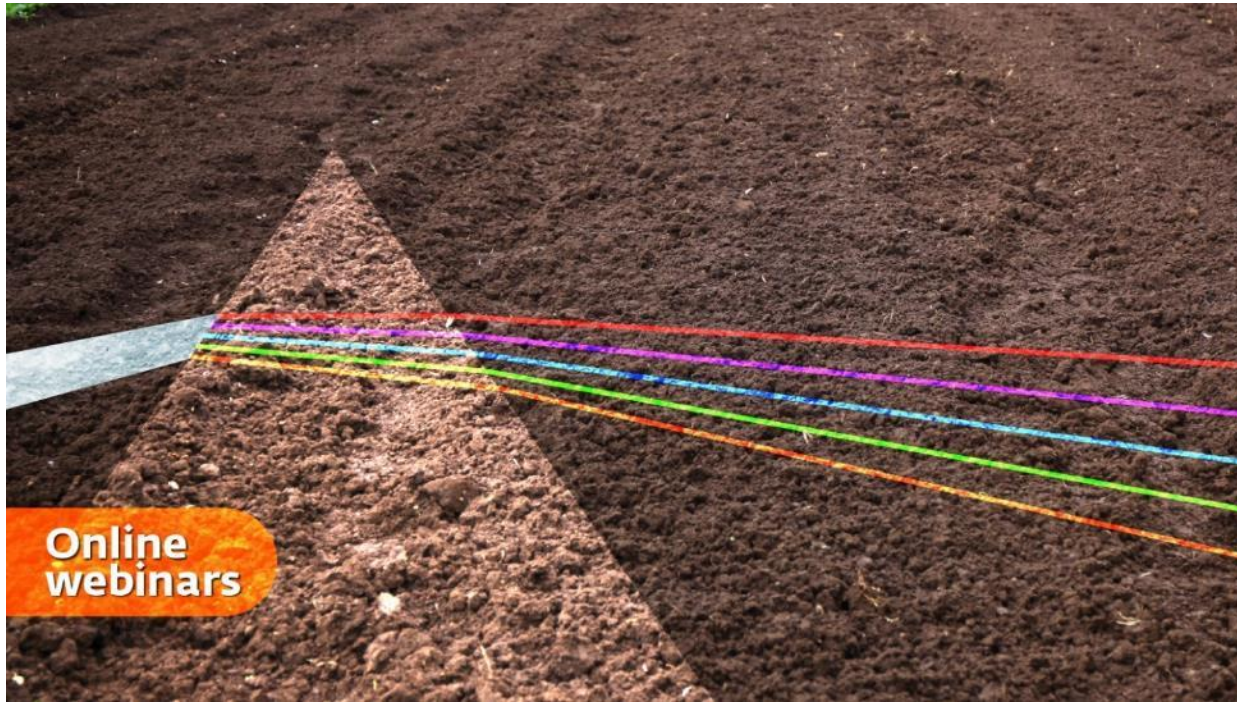
Barthes et al., 2020. Geoderma

Questions

- Which performances can we expect when the validation samples come from a region compared to Calibration samples coming from National area ?
- Which approach is appropriate in this specific situation?

Highlights

- ❖ The French dataset may provide accurate SIC prediction at regional scale from Global Model (« classical approach »)
- ❖ SIC predictions may be improved by using spiked samples and Local calibration (=Local-PLSR).
- ❖ Using the Local-PLSR approach with sufficient number of neighbours may allow to avoid bad predictions on some specific samples poorly represented in the National dataset.

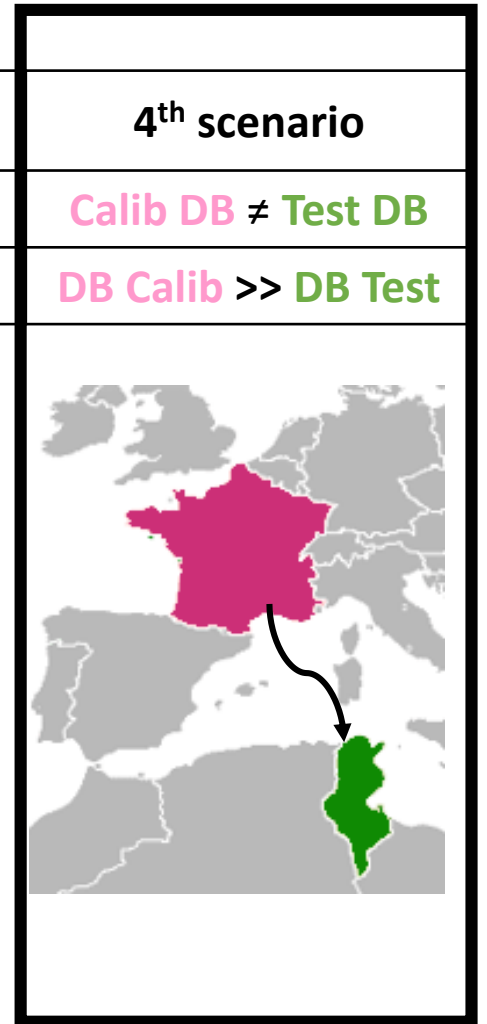
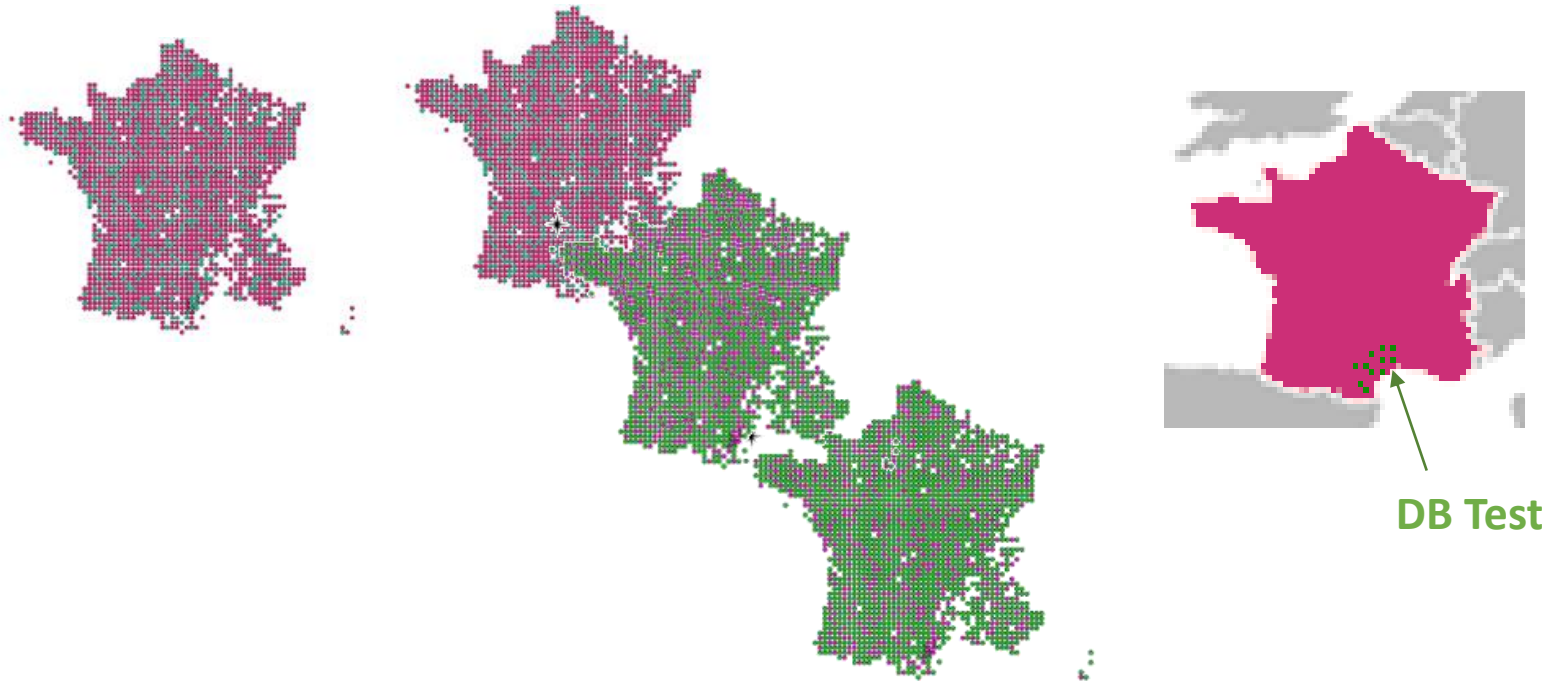


Can we use the French spectral library for soil properties estimation *at Regional Scale (Outside of France)?*

Can we use the French spectral library for soil properties estimation *at Regional Scale (Outside of France)?*

=> Scenario 4

	1 st scenario	2 nd scenario	3 rd scenario	4 th scenario
Area coverage	Calib DB = Test DB	Calib DB = Test DB	Test DB \in Calib DB	Calib DB \neq Test DB
Database sizes	Calib DB > Test DB	Nb Calib DB = 100% - Nb Calib DB	Calib DB \gg Test DB	DB Calib \gg DB Test



Questions

- Which performances can we expect when the validation samples come from a region **OUTSIDE** of the territory covered by the Calibration samples?
- Which approach is appropriate in this specific situation?



Gomez et al., 2020. Geoderma

Questions

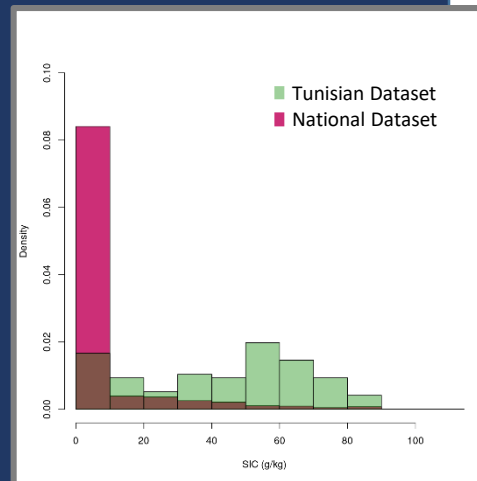
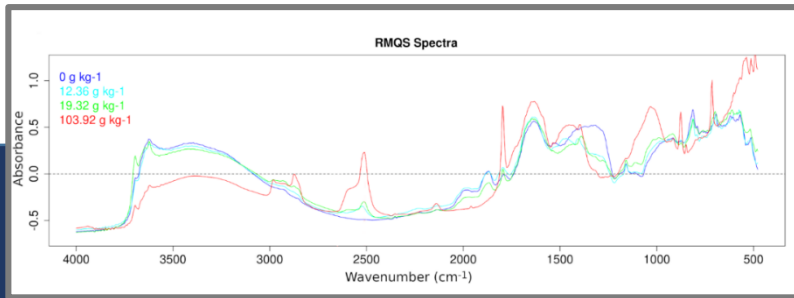
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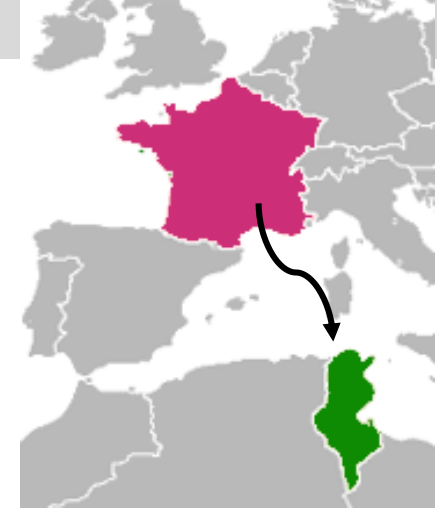


Gomez et al., 2020. *Geoderma*

Data

- ✓ 2178 soil samples of RMQS
Collected at 0-30 cm depth
- ✓ 96 soil samples from Tunisia
Collected at 0-10 cm depth
- ✓ MIRS spectra
- ✓ Soil Organic Carbon (SOC) and
Soil Inorganic Carbon (SIC)





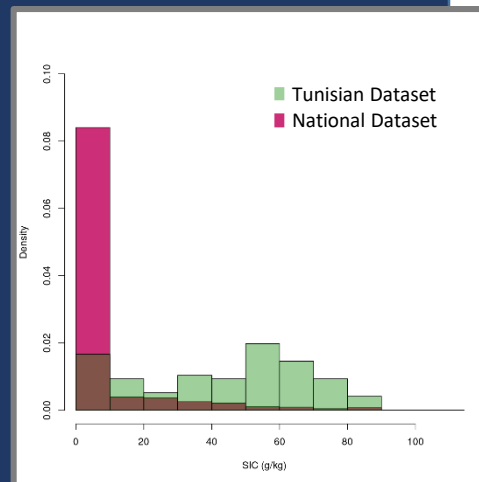
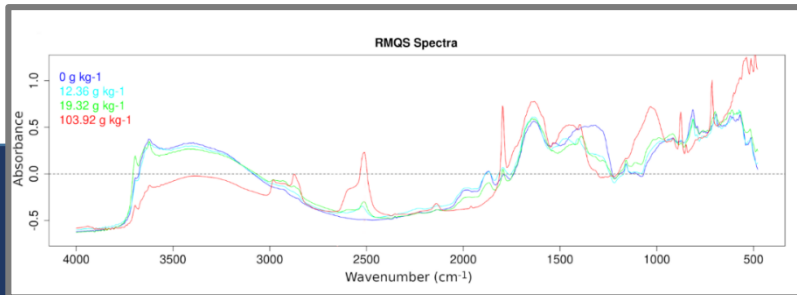
Gomez et al., 2020. Geoderma

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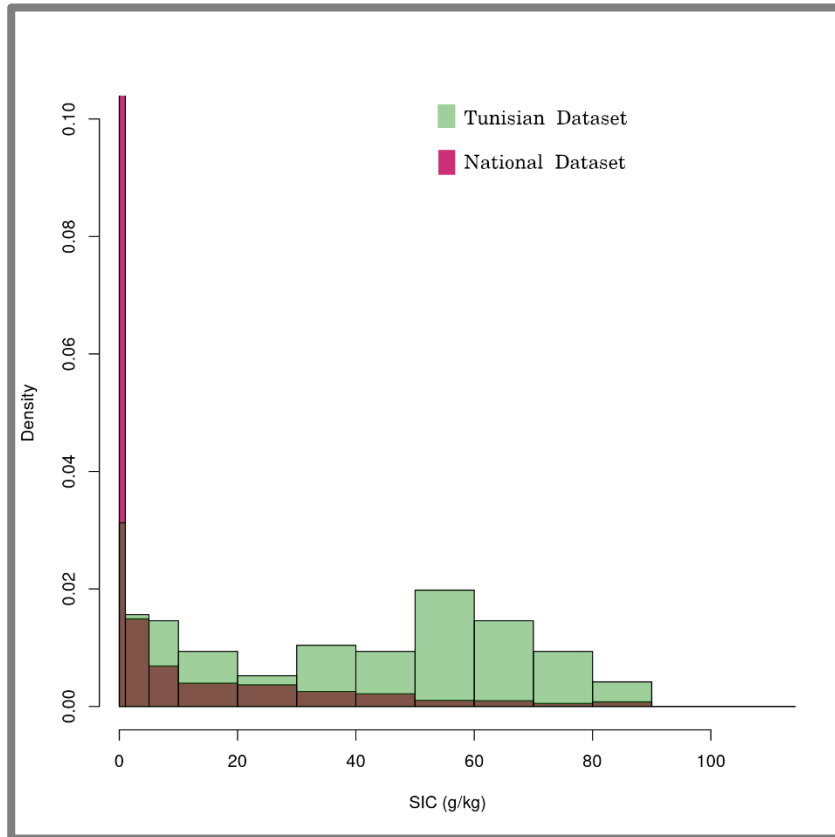
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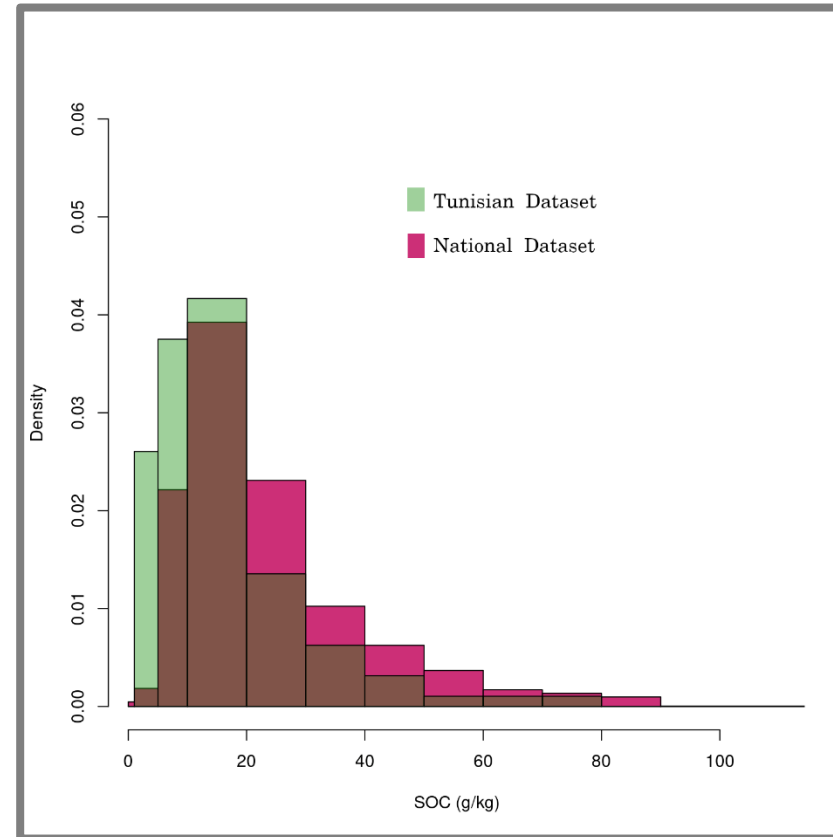


Methods

- ✓ PLSR to build regression models
- ✓ RMQS dataset divided in 75% for Calibration and 25 % for Validation
(same SOC and SIC distributions in both)
- ✓ 2 Tested Approaches. Calibration from
 - ❖ PLSR using all calibration soil samples of RMQS
 - ❖ PLSR using spectral neighbours of calibration dataset
- ✓ Test using the 96 Tunisian soil samples

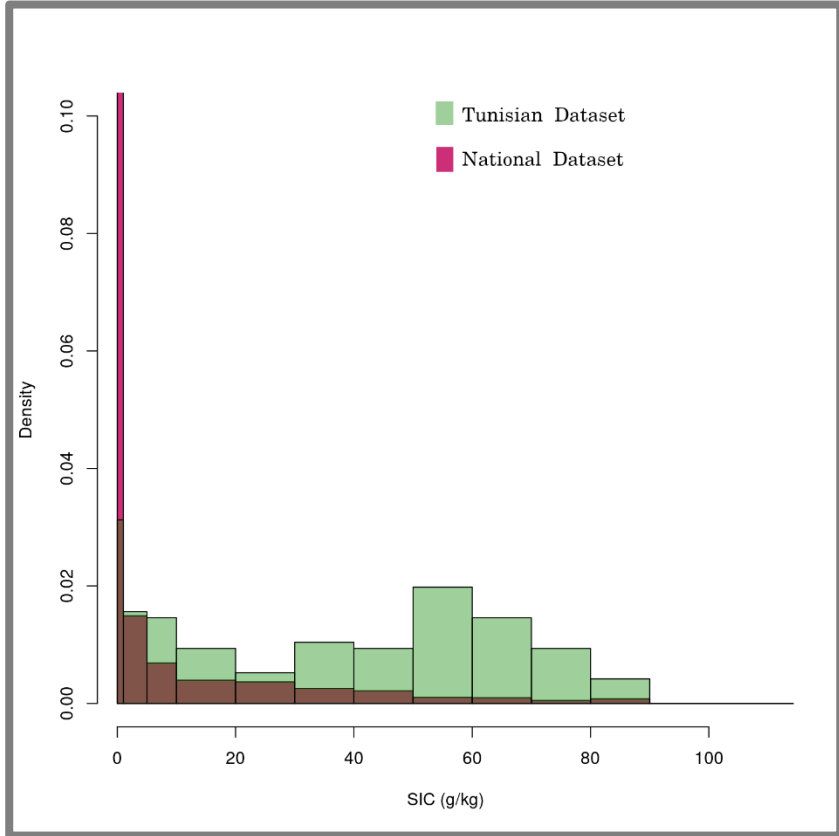
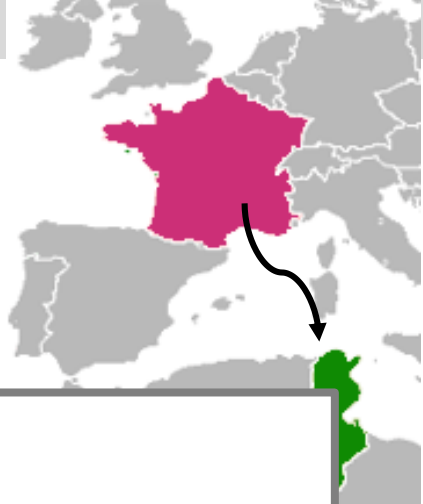


**Similar SIC ranges
but different SIC distributions**

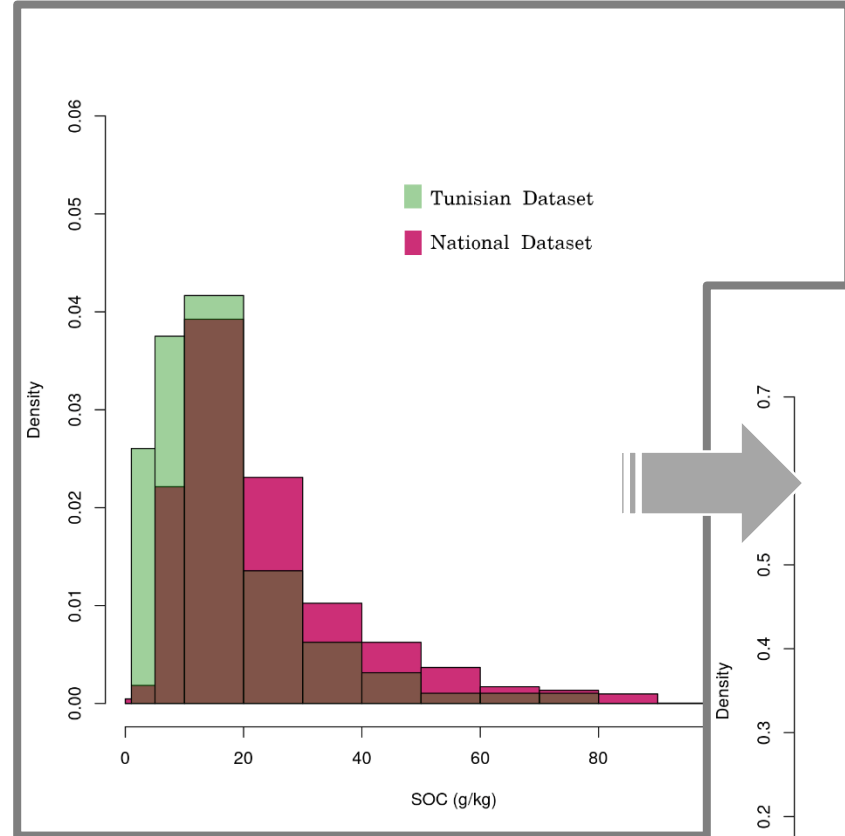


**Similar SOC ranges and
distributions**

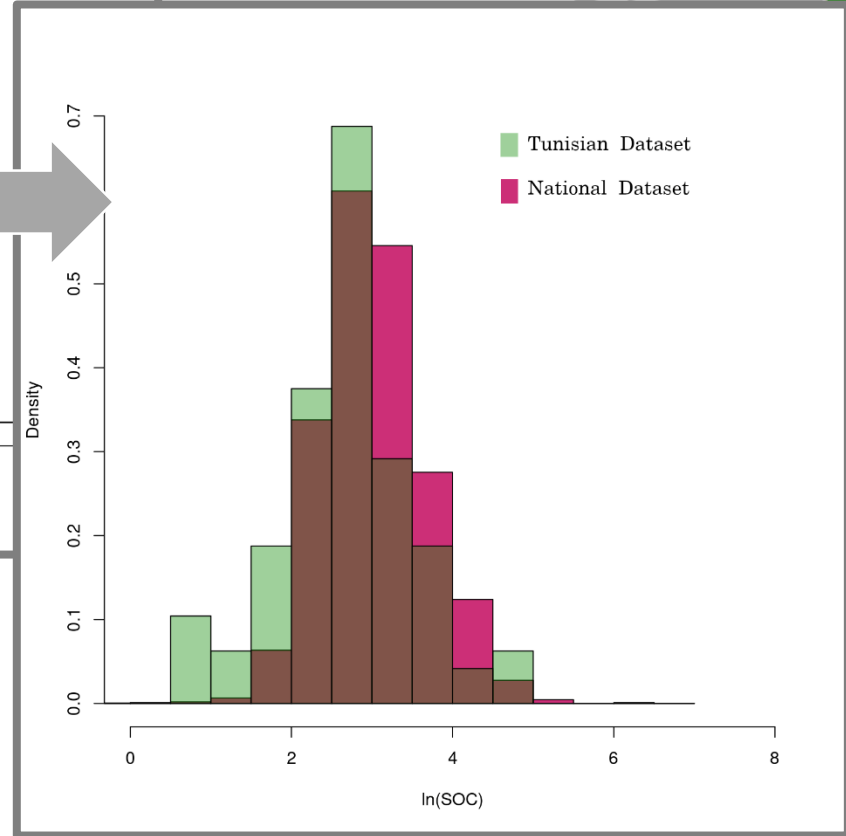
**=> non-normal distributions of SOC and SIC
contents for RMQS samples**



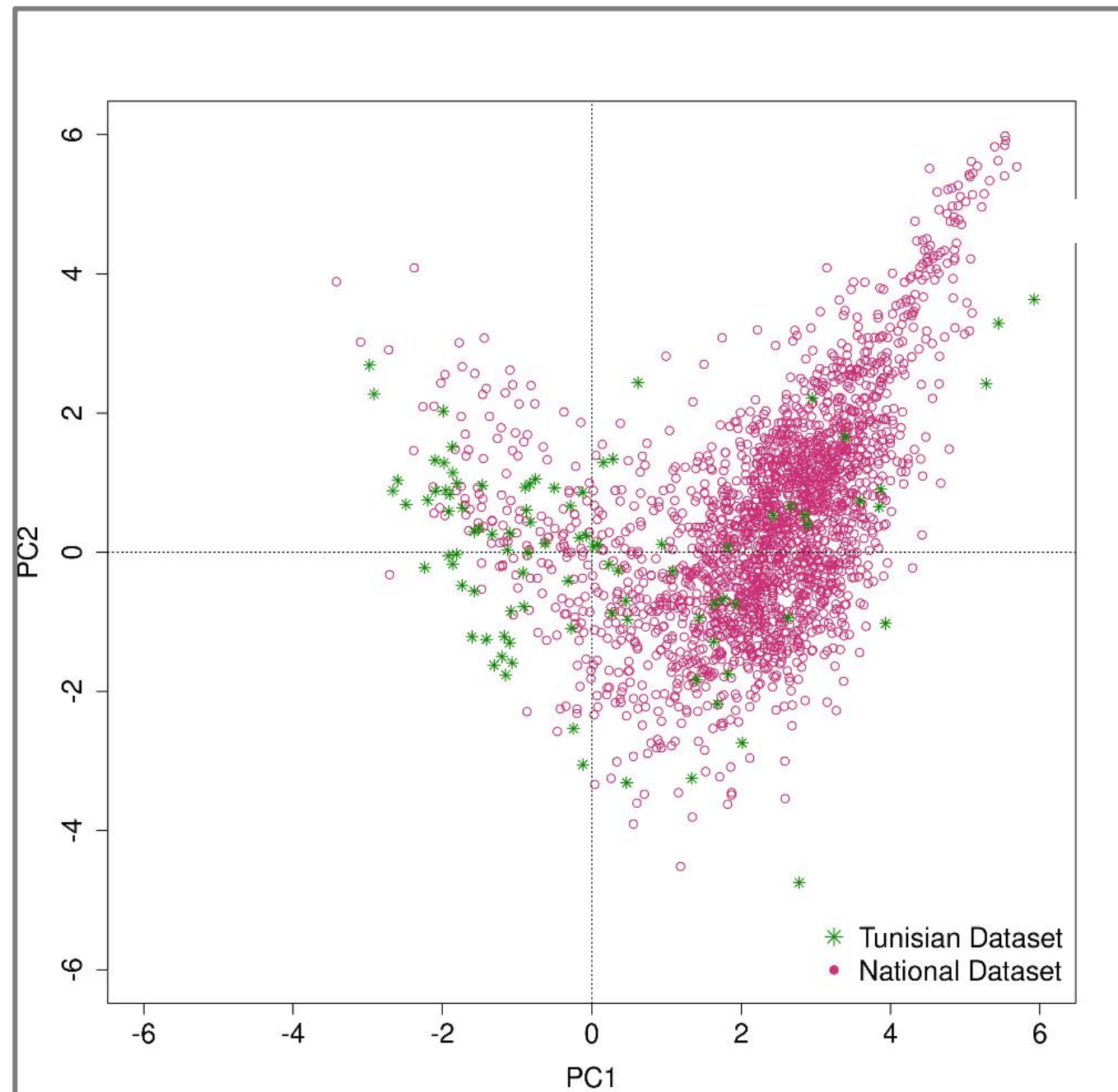
Similar SIC ranges but different SIC distributions



Similar SOC ranges and distributions



⇒ **Transformation to normal distribution of SOC content of RMQS samples**





	R^2_{val}	$RMSE_{val}$ g kg ⁻¹	RPD_{val}	R^2_{test}	$RMSE_{test}$ g kg ⁻¹	RPD_{test}
Global-Model for SIC predictions	0.98	2.1	7.6			
Global-Model for SOC predictions	0.88	7.2	2.7	0.64	16.0	1.3
Global-Model for ln(SOC) predictions*	0.90	6.6	2.9			



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Local-Model for SOC predictions	0.93	5.4	3.6	0.89	6.9	3.0
Global-Model for ln(SOC) predictions*	0.90	6.6	2.9	0.97	4.2	4.9
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Questions

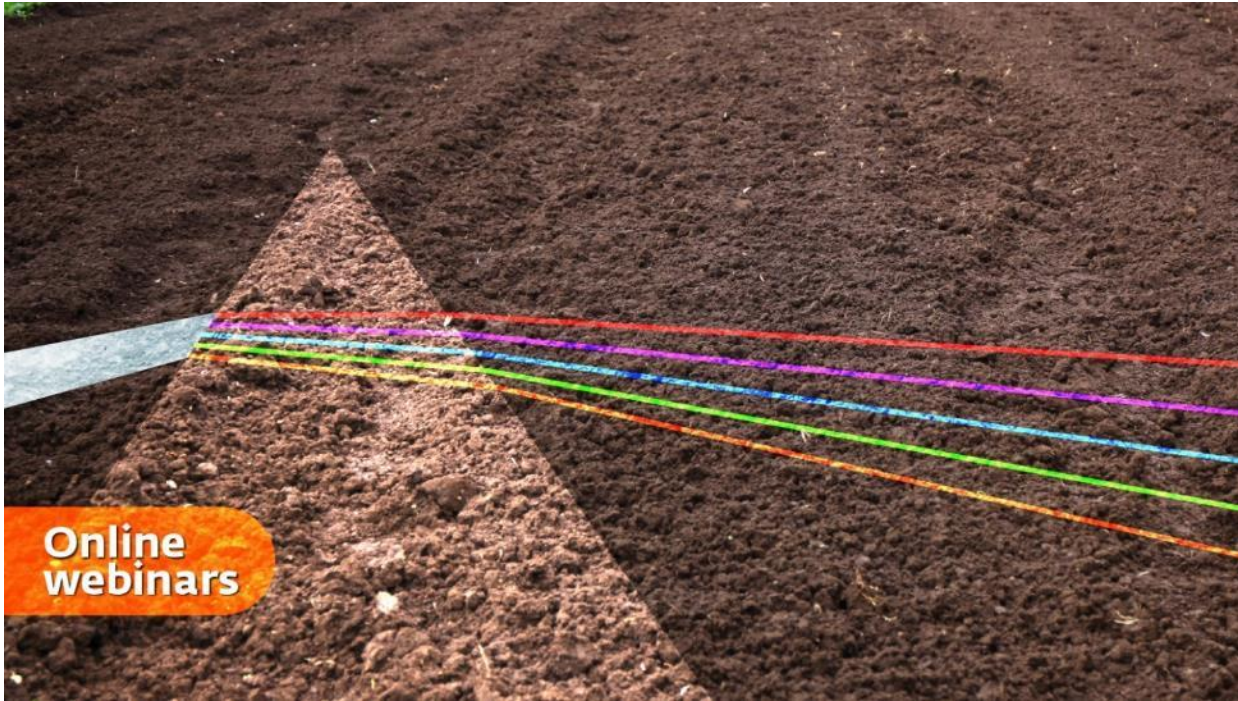
- Which performances can we expect when the validation samples come from a region **OUTSIDE** of the territory covered by the Calibration samples?
- Which approach is appropriate in this specific situation?



Gomez et al., 2020. Geoderma

Highlights

- MIRS is a promising tool for SIC determination, even when the calibration and test samples originate from different contexts....
 - ... while the SOC prediction performance decreases.
- Local calibration significantly improved SOC prediction of Tunisian samples.
- Log-transformation of SOC were more efficient than the local-model approach.



Main Highlights / Recommendations



Main Highlights

Development of a Danish national vis-NIR soil spectral library for soil organic carbon determination

M. Knadel, F. Deng, A. Thomsen, M.H.

Dept. of Agroecology, Faculty of Agricultural Sciences, Aarhus University
Blichers Alle 20, PO box 50, DK-8830 Tjele

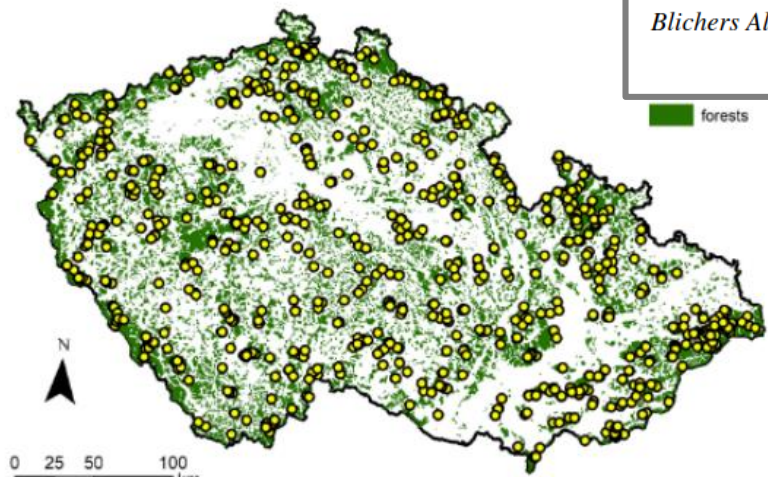


Fig. 1. Location of Czech forests and soil sampling sites.

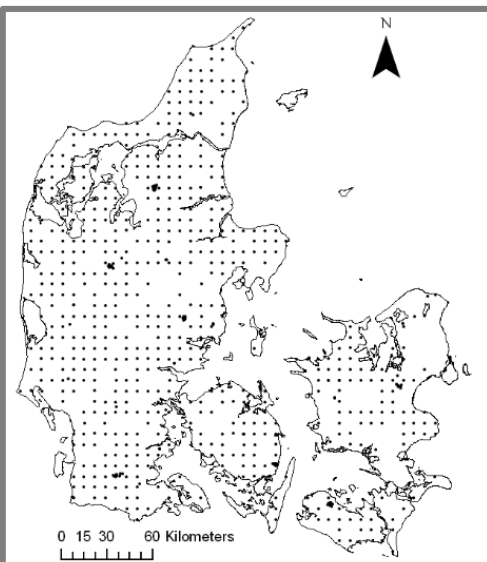


Figure 1. Distribution of soil profiles across Denmark.

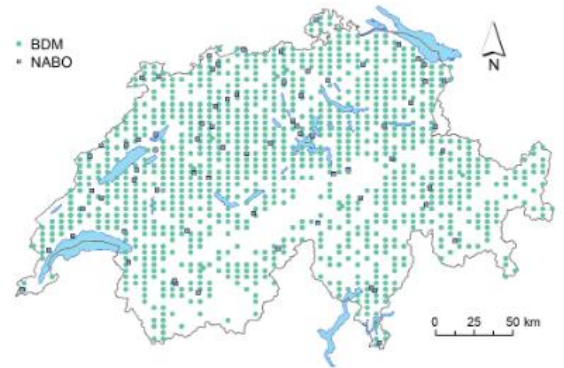
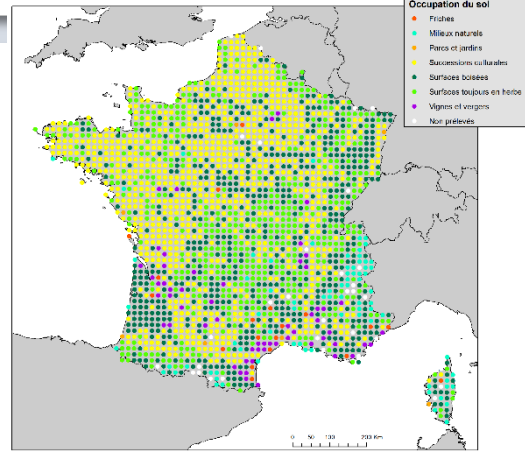


Figure 1. Map of Switzerland with sampling locations of the mid-IR spectral library, including the sites of the Biodiversity Monitoring program (BDM; 6 × 4 km; n = 1094) and the National Soil Monitoring Network (NABO; n = 71). In total, 71 NABO sites (10 m × 10 m) were sampled with a grid-based stratified design, and 1094 BDM samples were obtained from single sampling events. The NABO sites have been continuously sampled and measured in 5-year intervals since 1985.

SOIL, 7, 525-535
<https://doi.org/10.5194/soil-7-525-2021>
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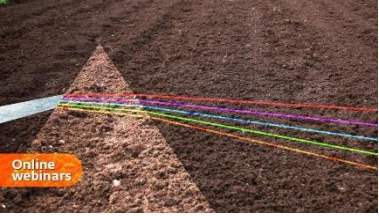
Geoderma
 journal homepage: www.elsevier.com/locate/geoderma

National-scale spectroscopic assessment of soil organic carbon in forests of the Czech Republic

Asa Gholizadeh^{a,*}, Raphael A. Viscarra Rossel^b, Mohammadmehdi Saberioon^c,
 Luboš Borůvka^a, Josef Kratina^a, Lenka Pavlů^a

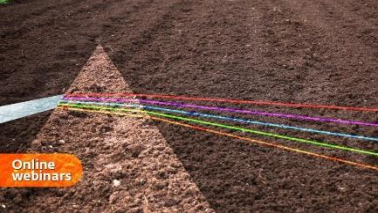
Developing the Swiss mid-infrared soil spectral library for local estimation and monitoring

Philipp Baumann^{1,2}, Anatol Helfenstein^{1,3}, Andreas Gubler⁴, Armin Keller², Reto Giulio Meuli⁴,
 Daniel Wächter⁴, Juhwan Lee⁵, Raphael Viscarra Rossel⁶, and Johan Six¹



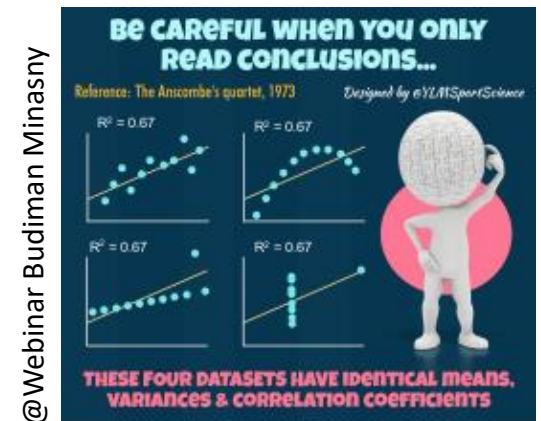
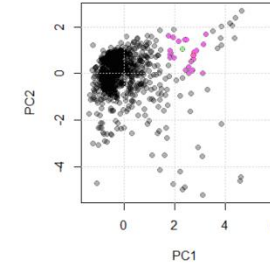
Main Highlights

- Current French National Dataset : ~3800 soil samples (collected every 16 km at two depth layers when feasible : 0-30 and 30-50 cm) associated to Vis-NIR, NIR, MIR spectra, soil attributes, soil biodiversity indicators...
- Future French National Dataset (collected every 16 km at four depth layers when feasible) :
 - > 7000 soil samples in 2030, > 11 000 in 2045, and > 15 000 in 2060
 - ⇒ *still associated to soil attributes*
 - ⇒ *NIR and/or MIR spectra would be also acquired*
- French National Dataset may provide soil properties predictions at both national and local scale for large-scale soil inventories and mapping studies
- Models using spectral neighbors (Local-PLSR) seem to be more appropriate than Global Models when using the French National Dataset



Main Highlights / Recommendations

- Have a look on test data (Spectra). Overlap Calibration data?
- Knowledge on pedological context of the test area. Same context than Calibration dataset?
- Define the aim of the soil properties predictions. Pre-classification of soils? Spatial pattern analysis? Monitoring?
⇒ so define the acceptable SEP for your study
- As explained by Budiman in a previous webinar, be careful to the R^2 !



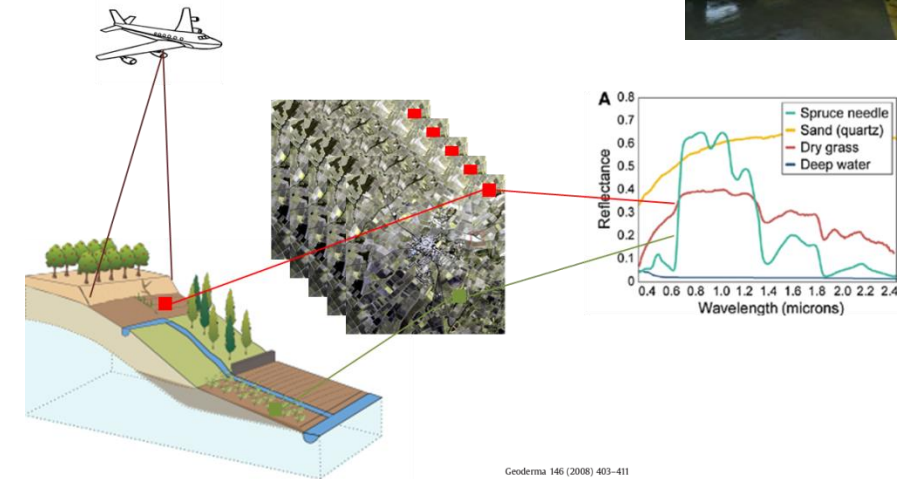
@Webinar Budiman Minasny



Main Highlights / Recommendations



- Remote sensing sensors acquire data in Vis-NIR range...
... and provide a synoptic view of the topsoil and a possible repetitive coverage
- Needs to go further in Vis-NIR developments to get benefit from the high quality of scattered Lab Vis-NIR spectra and the high quantity of remote sensing spectra



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Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study

Cécile Gomez ^{a,b,*}, Raphael A. Viscarra Rossel ^b, Alex B. McBratney ^b

^a IRD, Laboratoire d'étude des Interactions Sol-Agrosystème-Hydrosystème (LISAH), Campus AGR0-Box24, 34060 Montpellier, France
^b Australian Centre for Precision Agriculture, Food and Natural Resources, McMillan Building, A15, The University of Sydney, NSW 2006, Australia

High resolution topsoil mapping using hyperspectral image and field data in multivariate regression modeling procedures

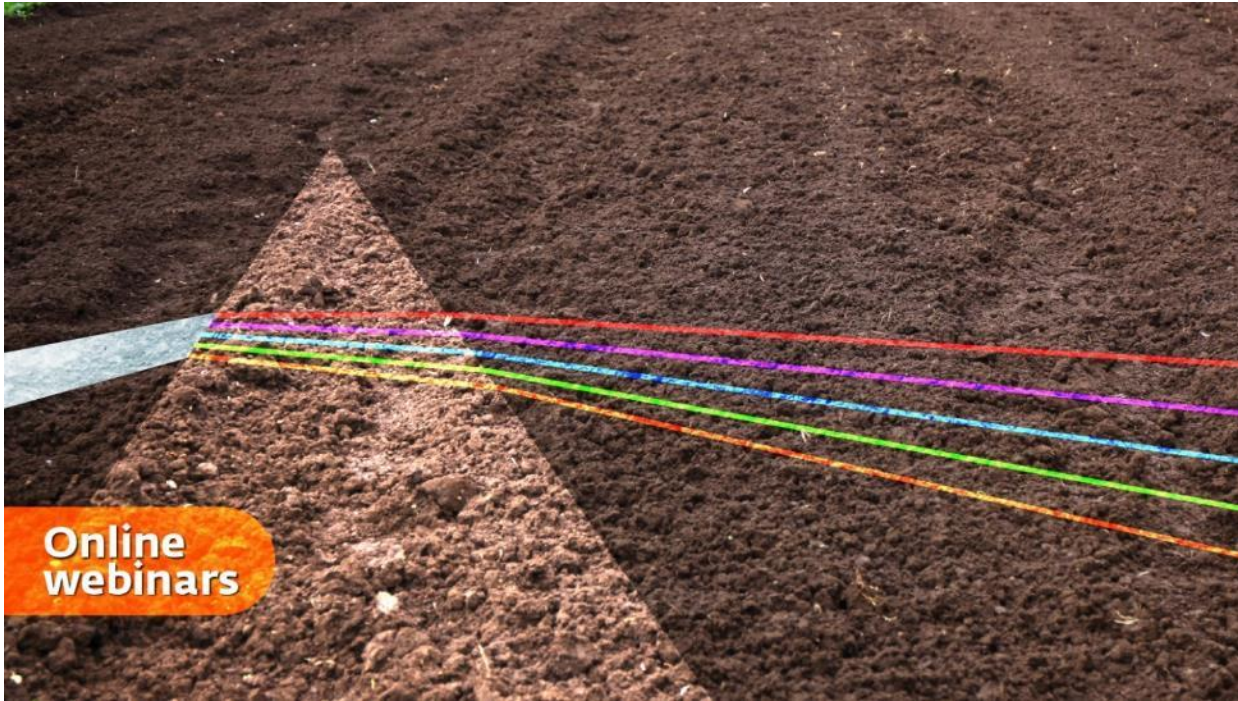
Thomas Selige ^{a,*}, Jürgen Böhner ^b, Urs Schmidhalter ^a

^a Chair of Plant Nutrition, Department of Plant Sciences, Technical University of Munich, Am Hochanger 2, D-85350 Freising,
^b Department of Physical Geography, University Göttingen, Goldschmidtstrasse 5, D-37077 Göttingen, Germany

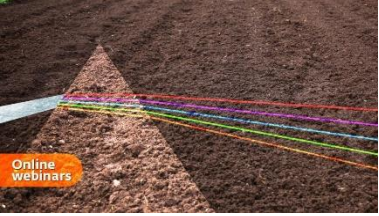
Measuring soil organic carbon in croplands at regional scale using airborne imaging spectroscopy

Antoine Stevens ^{a,*}, Thomas Udelhoven ^b, Antoine Denis ^c, Bernard Tychon ^c, Rocco Liroy ^d, Lucien Hoffmann ^b, Bas van Wesemael ^a

High potential for soil properties mapping
(% Clay, SOC, SIC, Iron, ...)



Next challenges?

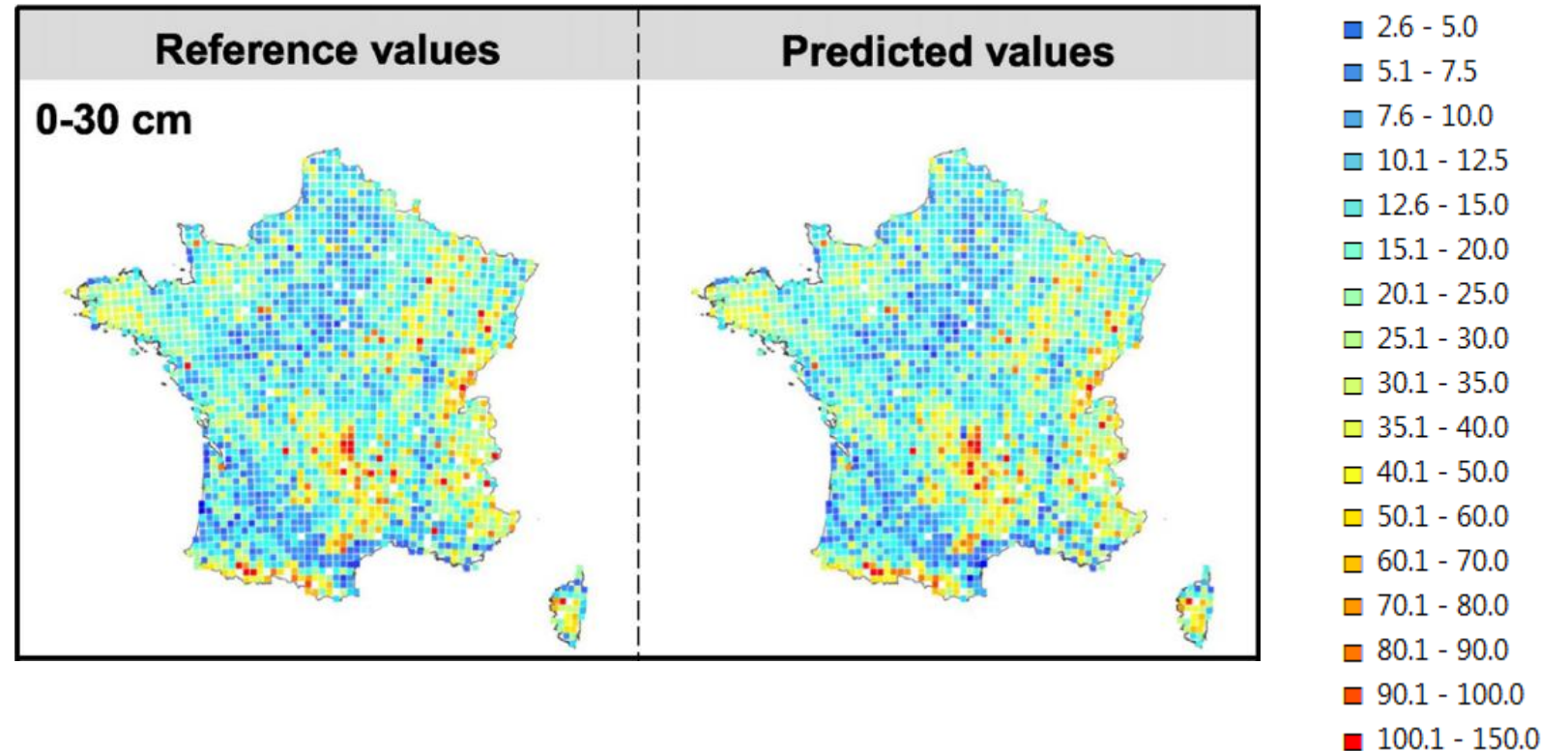


Next challenge?

Regarding the prediction errors, which temporal change of soil properties could we detect?

Soil Organic Carbon (g kg^{-1})

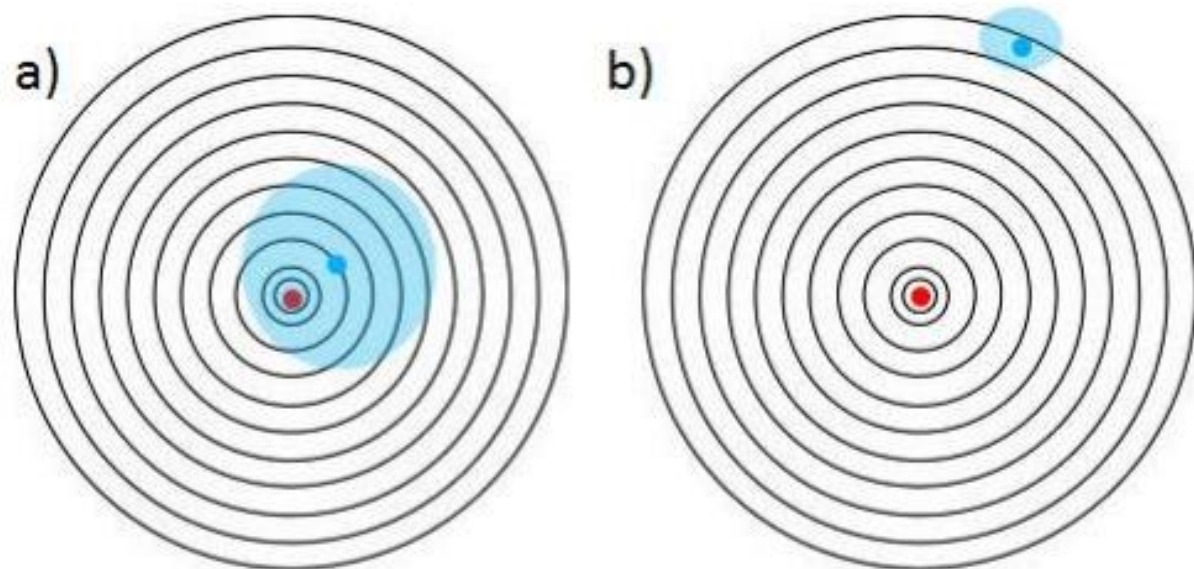
SEP = 4.7 g/kg



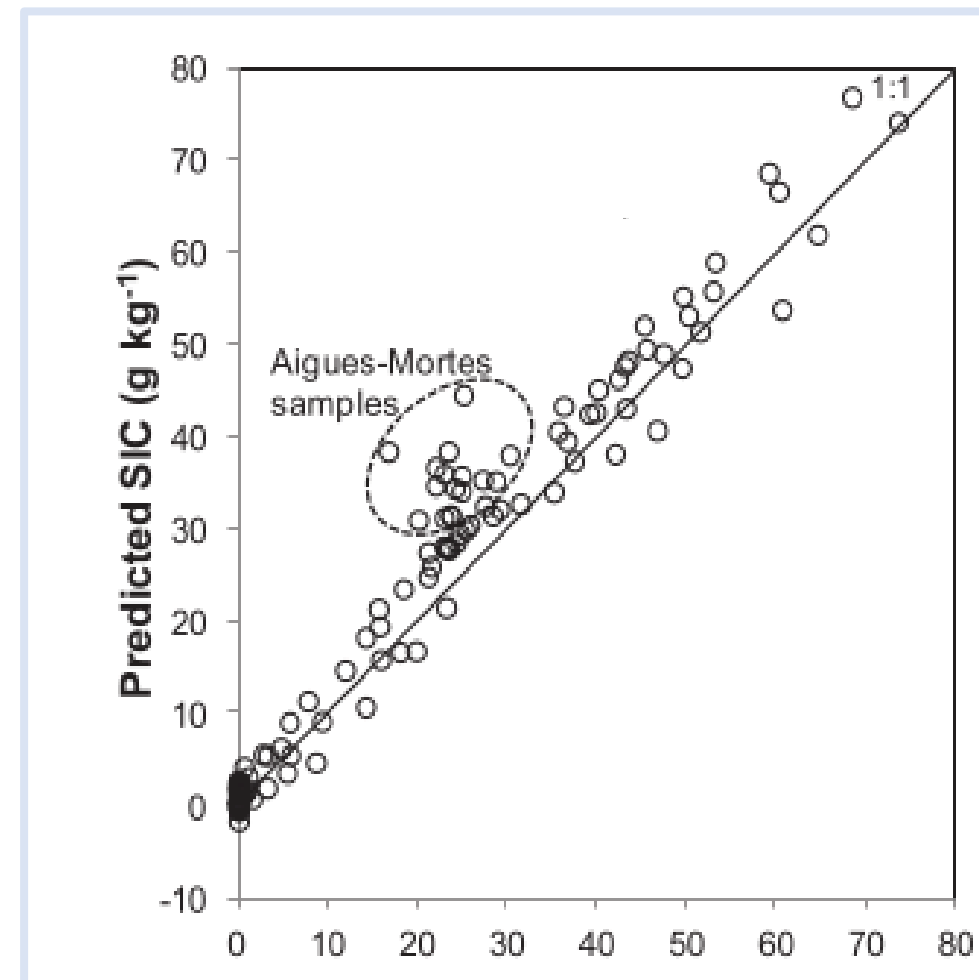


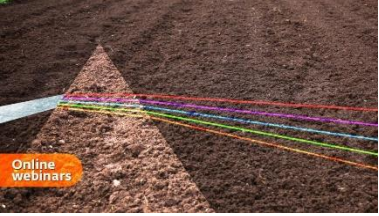
Next challenge?

Do we need to estimate an uncertainty and error to each new prediction?



- Measured soil property (Target)
- Estimated soil property
- Variance of estimated soil property





Next challenge?

Could we stop testing regression methods, pre-treatments, calibration data selection and fix a protocol to use this kind of dataset?

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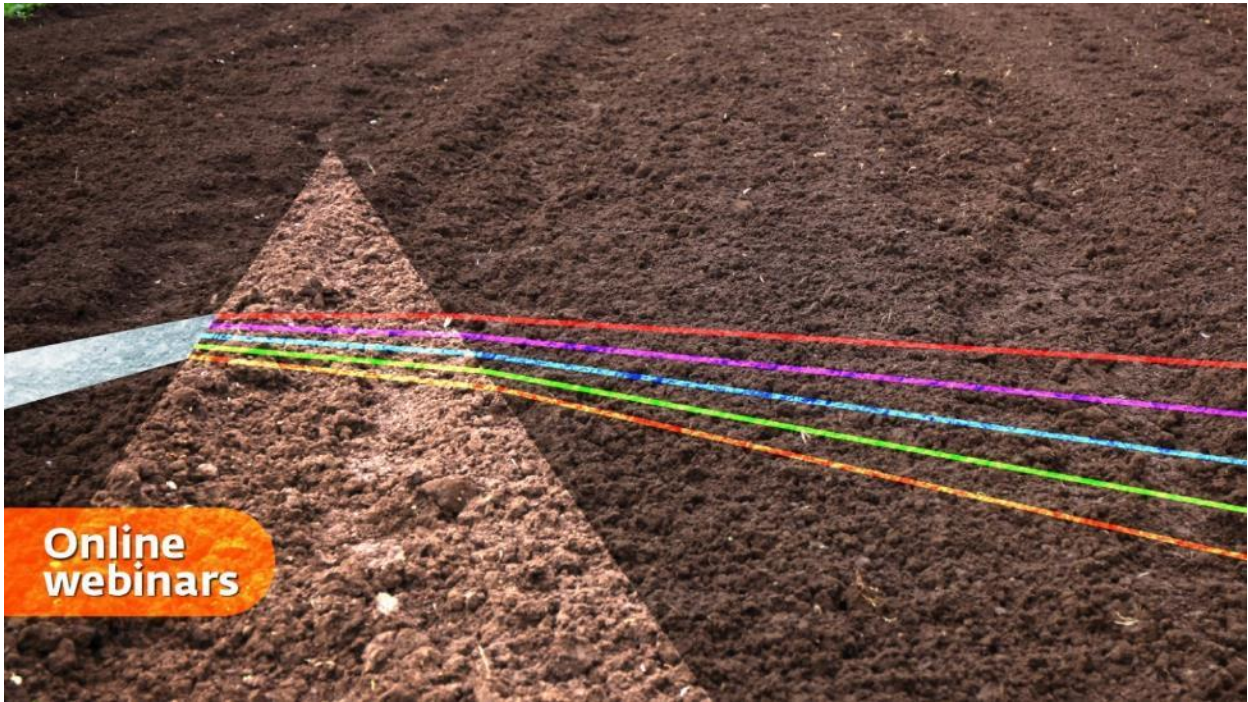


To spike or to localize? Strategies to improve the prediction of local soil properties using regional spectral library

Wartini Ng^{*}, Budiman Minasny, Edward Jones, Alex McBratney

School of Life and Environmental Sciences & Sydney Institute of Agriculture, The University of Sydney, NSW, Australia





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Acknowledgement



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Estimation of Soil Carbon Input in France: An Inverse Modelling Approach^{*1}

J. MEERSMANS^{1,*2}, M. P. MARTIN¹, E. LACARCE¹, T. G. ORTON¹, S. DE BAETS^{2,4}, M. GOURRAT¹, N. P. A. SABY¹, J. WETTERLIND¹, A. BISPO³, T. A. QUINE⁴ and D. ARROUAYS¹

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Statistical sampling design impact on predictive quality of harmonization functions between soil monitoring networks

B.P. Louis^{*}, N.P.A. Saby, T.G. Orton, E. Lacarce, L. Boulonne, C. Jolivet, C. Ratié, D. Arrouays



Impacts of national scale digital soil mapping programs in France

Dominique Arrouays^{a,*}, Anne C. Richer-de-Forges^a, Floren Songchao Chen^{a,c}, Manuel P. Martin^a, Mercedes Román Dobarco^a, Bertrand Laroche^a, Thomas Loiseau^a, Isabelle Cousin^e, M. Christine Le Bas^a, Thomas Eglin^f, Marion Bardy^g, Véronique Céline Ratié^a, Antonio Bispo^a

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Pedotransfer functions for predicting available water capacity in French soils, their applicability domain and associated uncertainty

Mercedes Román Dobarco^{a,*}, Isabelle Cousin^b, Christine Le Bas^a, Manuel P. Martin^a

Developing pedotransfer functions to harmonize extractable soil phosphorus content measured with different methods: A case study across the mainland of France

Bifeng Hu^{a,b}, Hocine Bourennane^b, Dominique Arrouays^a, Pascal Denoroy^c, Blandine Lemerrier^d, P.A. Saby^{a,*}

Assessment of diffuse contamination of agricultural soil by copper in Aquitaine region by using French national databases

Hind El Hadri^{a,b,*}, Philippe Chéry^b, Stéphanie Jalabert^b, Alexandre Lee^b, Martine Potin-Gautier^a, Gaëtane Lespes^a

Science of the Total Environment 441 (2012) 239–247

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Chemosphere 181 (2017) 635–644

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Chemosphere

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A survey of topsoil arsenic and mercury concentrations across France

B.P. Marchant^{a,*}, N.P.A. Saby^b, D. Arrouays^b

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^b INRA, US1106 Unité Infosol, Orléans, France

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M. Lacoste^{a,*}, V.L. Mulder^b, A.C. Richer-de-Forges^b, M.P. Martin^b, D. Arrouays^b

Prediction of total silicon concentrations in French soils using pedotransfer functions from mid-infrared spectrum and pedological attributes

A. Landré^a, N.P.A. Saby^{a,*}, B.G. Barthès^b, C. Ratié^a, A. Guerin^c, A. Etayo^c, B. Minasny^d, M. Bardy^a, J.-D. Meunier^e, S. Cornu^e

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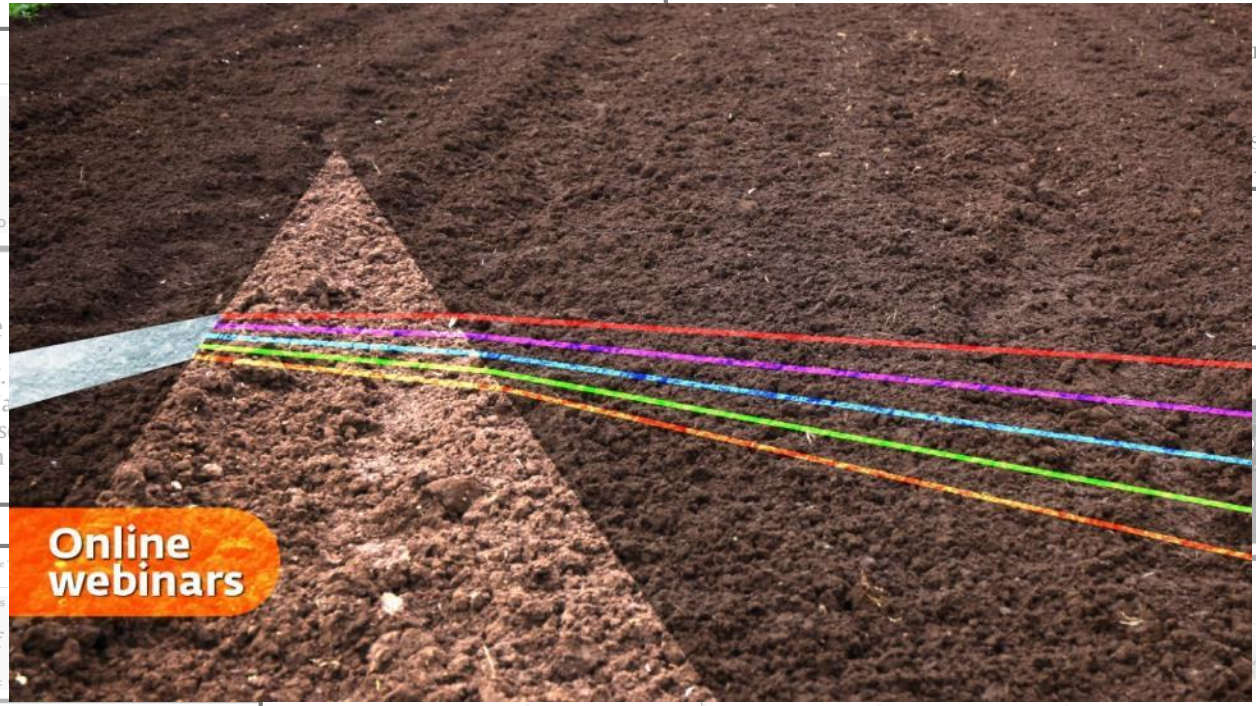
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