Spectroscopy-supported digital soil mapping

Outline

- Introduction
- Project and theoretical background
- Field sampling
- Estimating and mapping soil mineralogy
- Conclusion & outlook

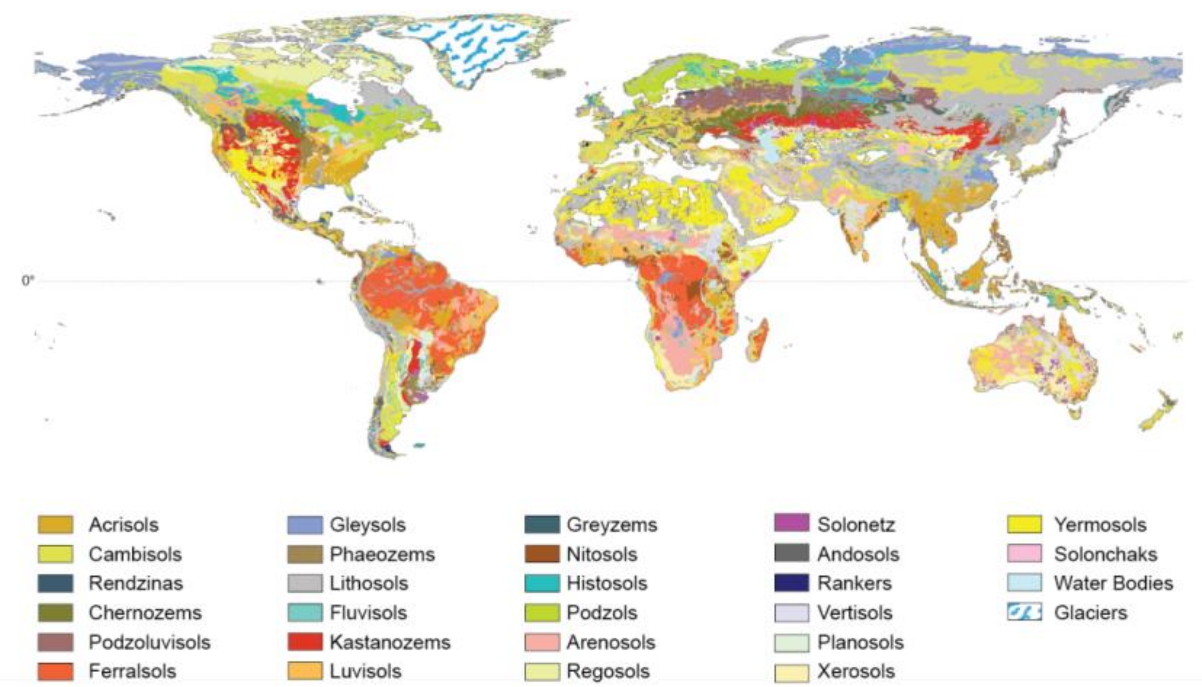
The nation that destroys its soils destroys itself

Frankling D. Roosevelt, Letter to all State Governors on a Uniform Soil Conservation Law (26 February, 1937)

BACKGROUND

In the epoch of the Anthropocene, human-driven changes affected the **functioning of the Earth System**. Nowadays, we need to adapt to climate changes and assure **food security** for the growing human population. Here, **soil resources** provide key ecosystem services and they need to be **mapped** and **monitored** on regional and global scale.

Source: Sustainable Development Solutions Network, United Nations, Solutions for sustainable agriculture and food systems, 2013.



Problems

- Missing data and too general information
- Low accuracy
- How to use soil classes for modelling environmental processes

Source: FAO Soil map of the World

e-SOTER: enhanced Soil and Terrain Database

- Regional soil and terrain mapping
- Web-based *regional pilot platform*
- Data, methodologies, and applications
- Using remote sensing to validate, augment and extend existing data

OBJECTIVE

To exploit the use of **remote** (RS) and **proximal sensing** (PS) methodologies for **digital soil mapping** (DSM) to facilitate soil property mapping at **regional** scale.

Digital soil mapping

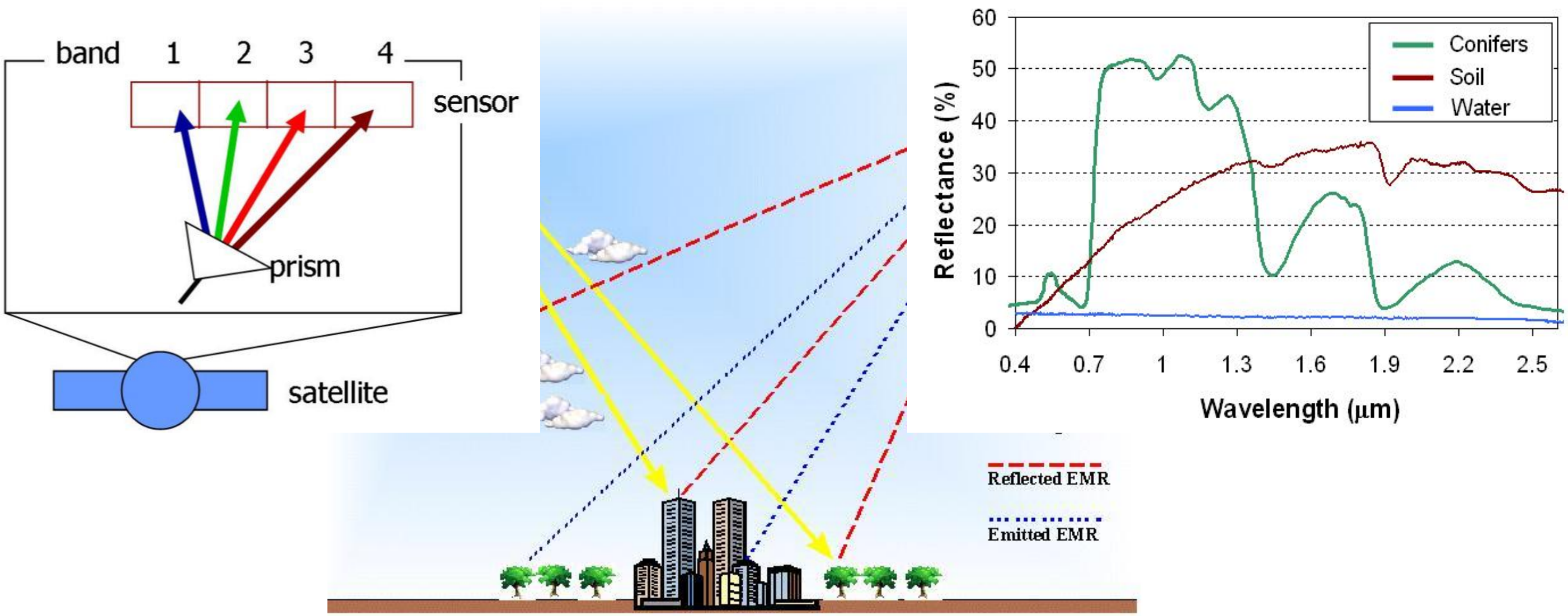
The creation and population of spatial soil information by the use of field and laboratory observation methods coupled with spatial and non-spatial soil inference systems

(Carré et al., 2007)

1. Goal: Spatial patterns of soils across various spatial and temporal scales
2. Local soil observations
   - Field, laboratory and PS observations
3. Exhaustive datasets
   - Spatially explicit maps, e.g. existing soil maps or RS data & product
4. Statistical methods
   - Regression models
   - Data mining
   - Geostatistics

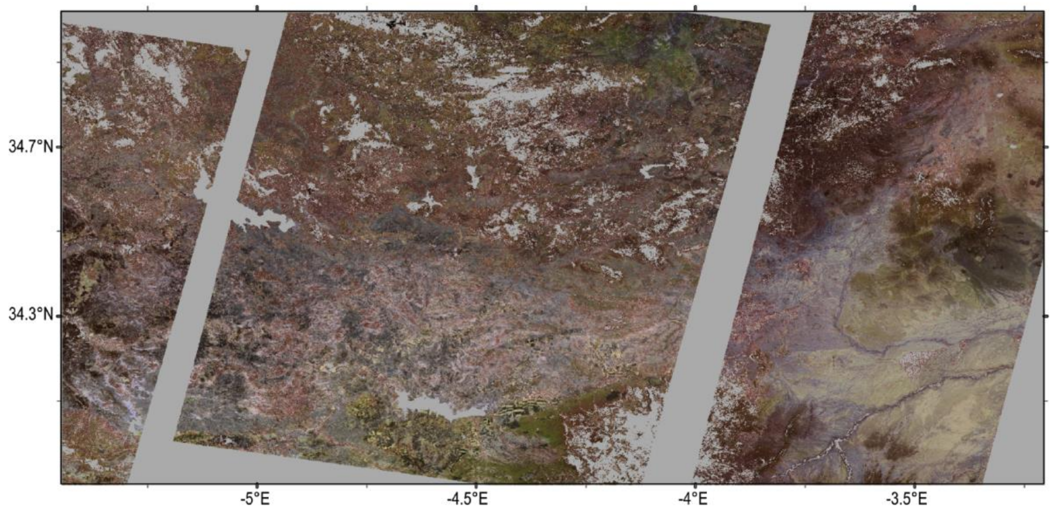
F. Carré, A.B., McBratney, T. Mayr, L. Montanarella (2007). Digital soil assessments: Beyond DSM. Geoderma, 142 (1-2), 69-79.

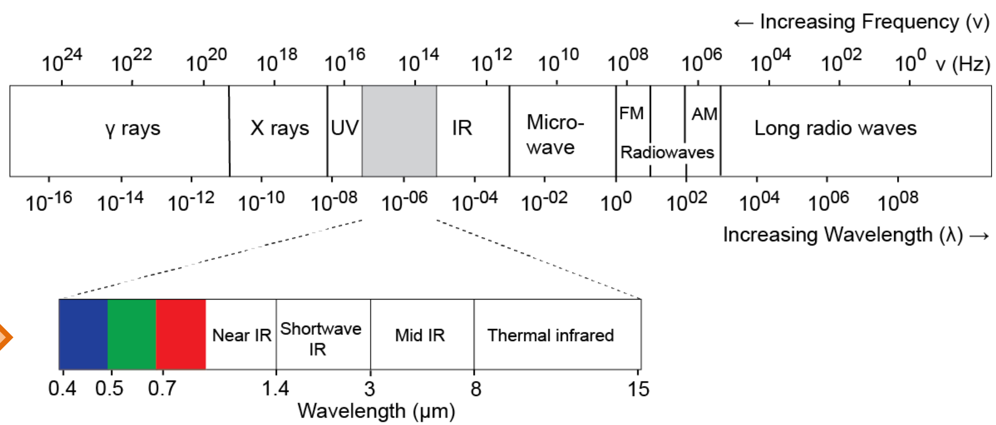
Remote Sensing



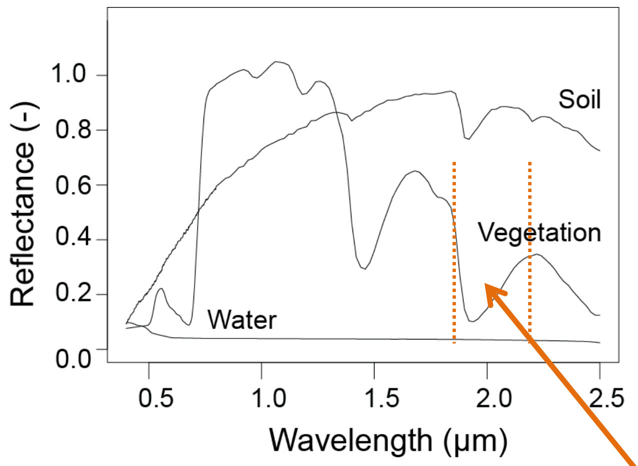
- RS is the science/ are the techniques of deriving information about the Earth's land and water areas from images at a distance
- It relies upon measurement of electro-magnetic (EM) energy reflected or emitted from the objects of interest at the surface of the Earth

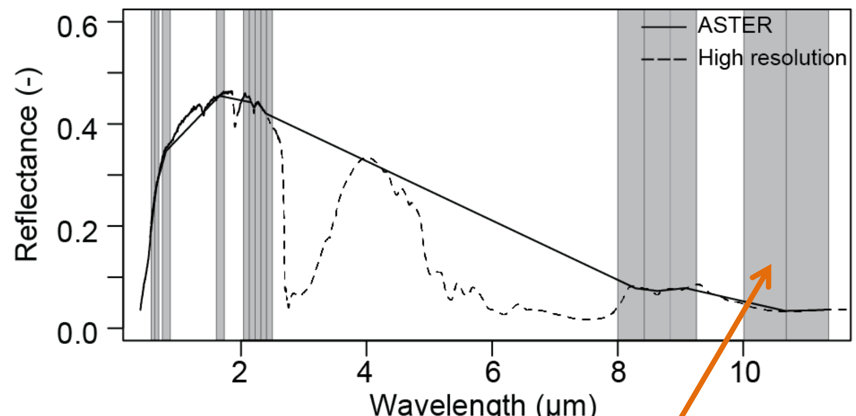
Remote and proximal sensing





Remote and proximal sensing

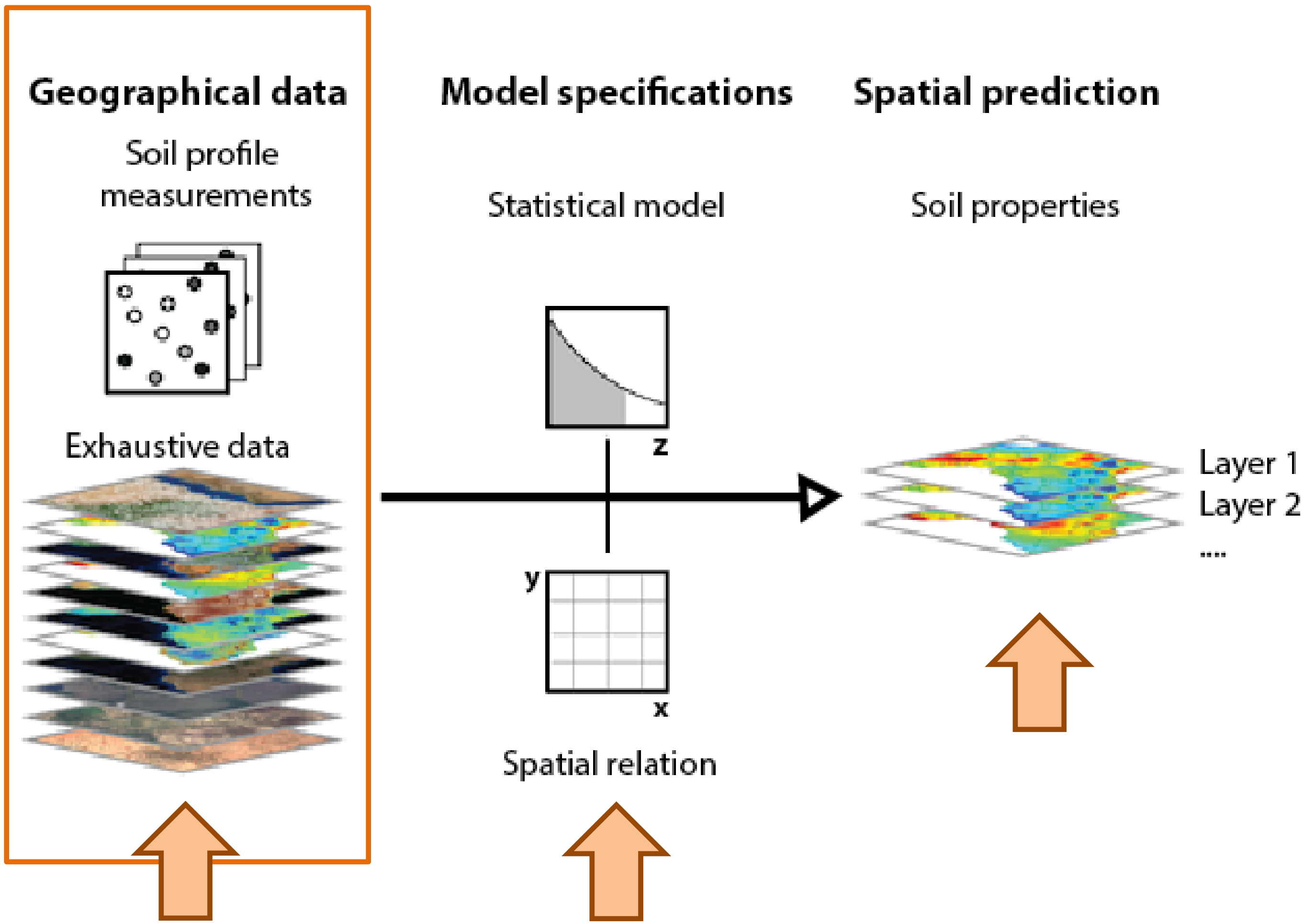




Absorption feature

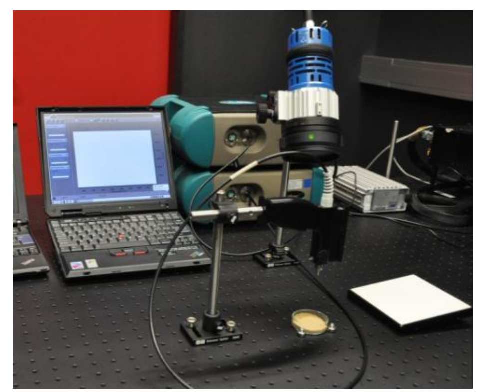
Broad bands

Workflow digital soil mapping (DSM)



Source: Africa Soil Information Service,
http://www.africasoils.net/data/digital-soil-mapping

Spectroscopy-supported digital soil mapping (I)

	Traditional	Spectroscopy
Data collection	 Fieldwork Maroc: soil profile description	 Fieldwork Maroc: Spectral measurements
Soil measurements	 Laboratory measurements: X-ray diffraction	 Laboratory measurements: Spectral measurements

V.L. Mulder, S. de Bruin, M.E. Schaepman, T.R. Mayr (2011). The use of remote sensing in soil and terrain mapping – A review. Geoderma, 162- (1-2), 1-19. doi:10.1016/j.geoderm.2010.12.018

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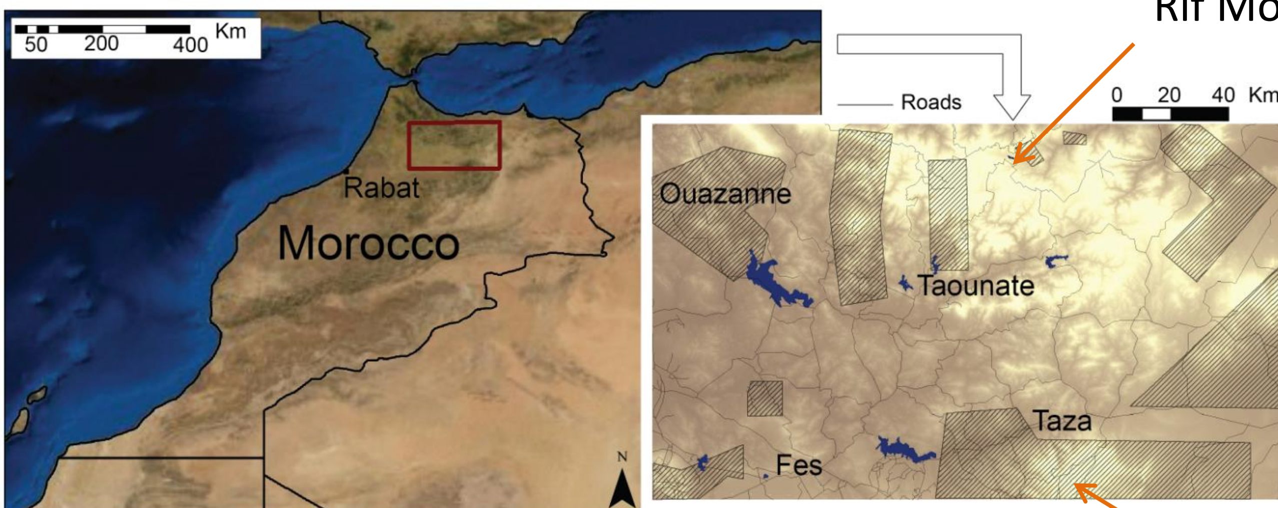
What is the current state-of-art in the use of remote sensing for soil and terrain mapping?

Use		Proximal Sensing	Remote sensing
Estimating soil properties:			
	Quantitative Qualitative	**+/-** **+**	**-** **+**
Characterizing the landscape		**-**	**+**
Spatial interpolation		**-**	**+**
Associated spatial scale		**Point - Local**	**Local - Global**

V.L. Mulder, S. de Bruin, M.E. Schaepman, T.R. Mayr (2011). The use of remote sensing in soil and terrain mapping – A review. Geoderma, 162- (1-2), 1-19. doi:10.1016/j.geoderm.2010.12.018

Study area

Rif Mountains



Anti-Atlas Mountains

V.L. Mulder, S. de Bruin, M.E. Schaepman (2012). Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data. International Journal of Applied Earth Observation and Geoinformation, (21) 301-310. doi:10.1016/j.jag.2012.07.004

Topography

Fertility

Source: Fieldwork campaign Maroc, 2010

MAIN FINDINGS

- 2 weeks in the field
- Few legacy data
- 150.000 km2
- Time & financial limitations

SAMPLING

Can **major soil variability** at regional scale be represented by a sparse remote sensing-based sampling approach?

V.L. Mulder, S. de Bruin, M.E. Schaepman (2012). Representing major soil variability at regional scale by constrained Latin Hypercube Samping of remote sensing data. International Journal of Applied Earth Observation and Geoinformation, (21) 301-310. doi:10.1016/j.jag.2012.07.004

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Soil-landscape paradigm (Jenny)

Soil formation = **C**limate, **O**rganisms, **R**elief, **P**arent material & **T**ime (**CLORPT**)

Reflectance + elevation represents **CLORPT**

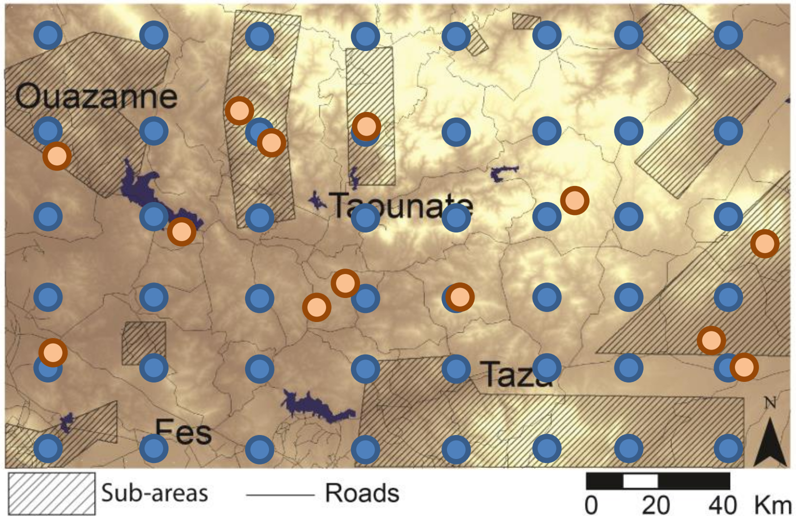
Latin Hypercube sampling

- Input: **Satellite** and **elevation** data as a variability measure of soils
- Constrained by subareas, distance to the roads and steepness of the landscape
    - Cost function f(x)= areas + distance + topography + water
- **100 sites** were optimised to optimally sample the Latin Hypercube (LH)
    - Minimize cost while sampling the marginal distributions within the LH
- The sample provides thematic information (fit prediction models)
- The RS data provides the necessary spatial context (extrapolation to full spatial extend)

V.L. Mulder, S. de Bruin, M.E. Schaepman (2012). Representing major soil variability at regional scale by constrained Latin Hypercube Samping of remote sensing data. International Journal of Applied Earth Observation and Geoinformation, (21) 301-310. doi:10.1016/j.jag.2012.07.004

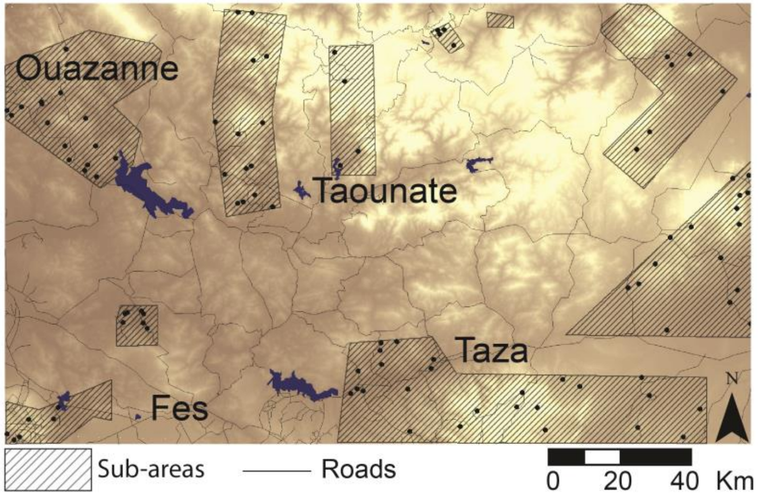
Sampling

Common practise



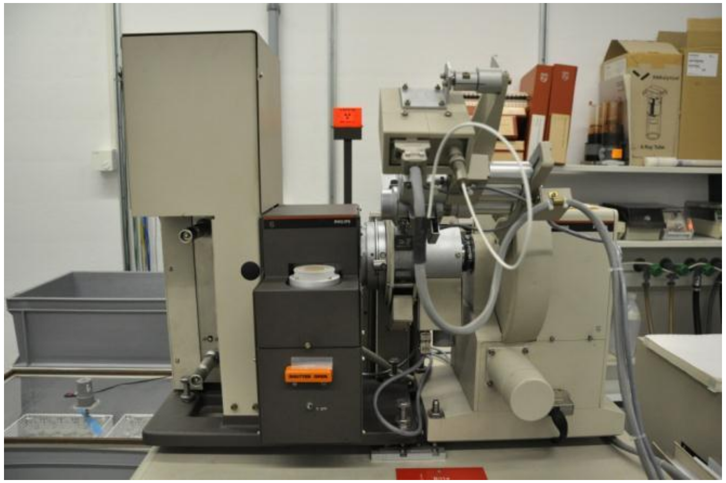
- Expensive
- Accessibility
- Sampled variability

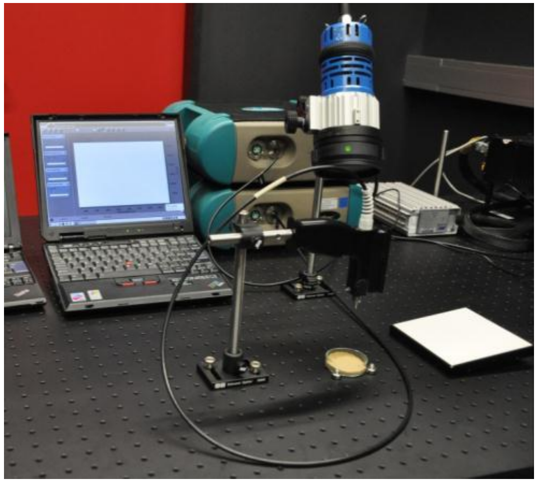
RS-based sampling approach



- Variability observed in RS data (PCA)
- Subareas, distance to road, steepness of the landscape
- Captured **major soil variability** in study area

V.L. Mulder, S. de Bruin, M.E. Schaepman (2012). Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data. International Journal of Applied Earth Observation and Geoinformation, (21) 301-310. doi:10.1016/j.jag.2012.07.004





RETRIEVAL

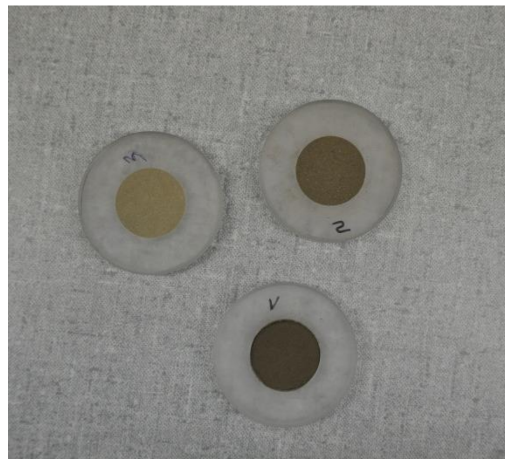
Which methods allow retrieval of **mineralogy** from **mixtures** using **proximal sensing**?

Measurements (I)

Field

Source: Canadian Wildlife federation

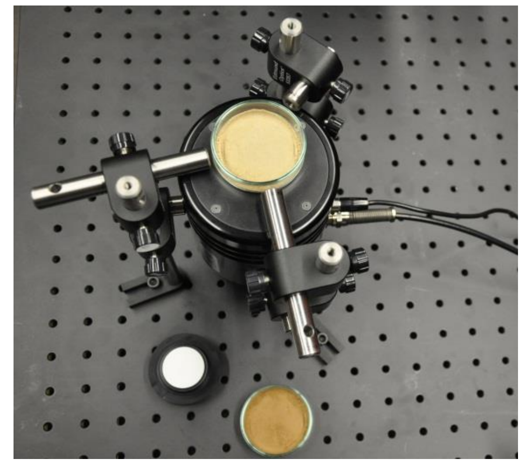
Standard analysis



Prepared samples for X-ray diffraction

OR

Spectral analysis



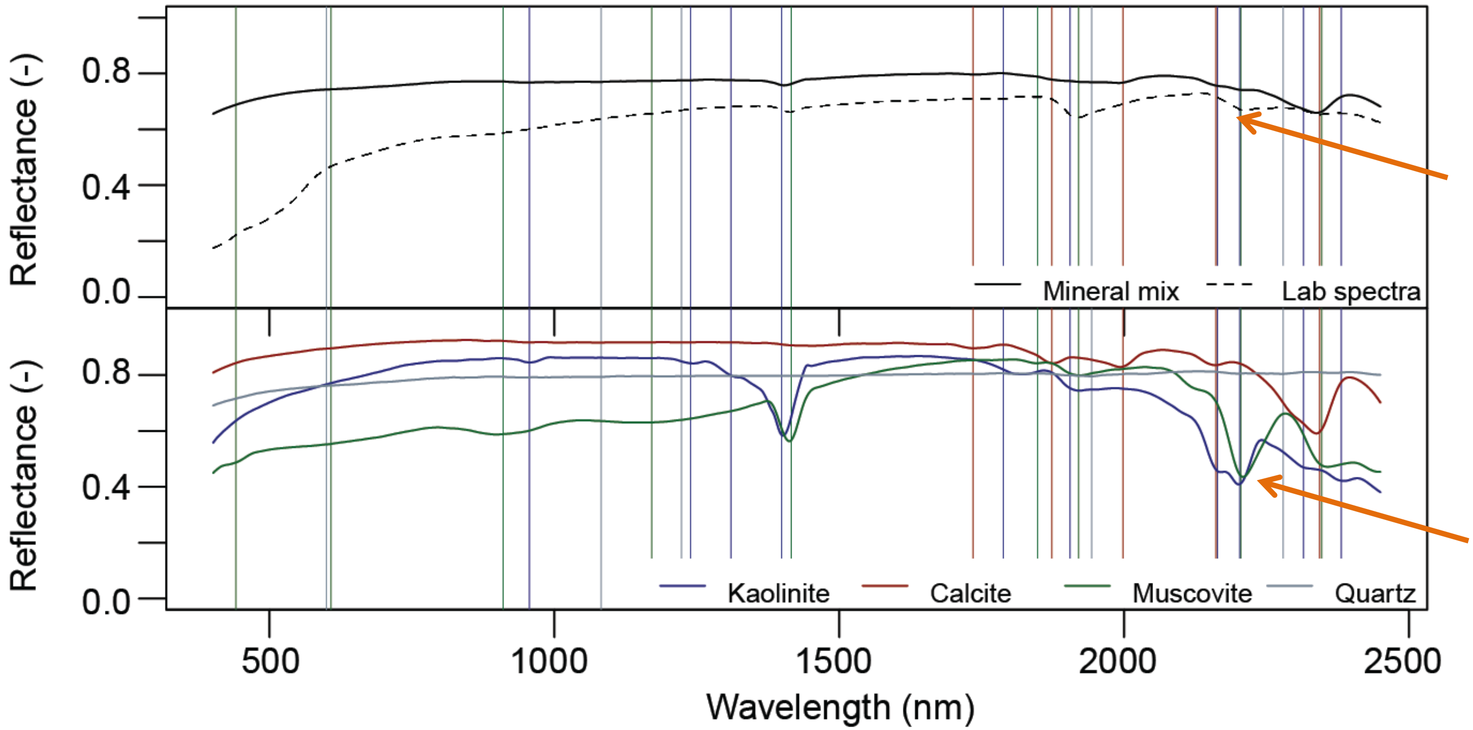
Prepared samples for spectroscopic measurements

Measurements of soil properties using spectroscopy

- Soil mineralogy
- Experiment 1: Classification of mineral classes
- Experiment 2: Retrieval of individual mineral abundances

Mineral maps?

Experiment 1: V.L. Mulder, S de Bruin, M.E. Schaepman, (2012). Retrieval of composite mineralogy by VNIR spectroscopy, 5th Global Workshop on Digital Soil Mapping 2012, Sydney, Australia.

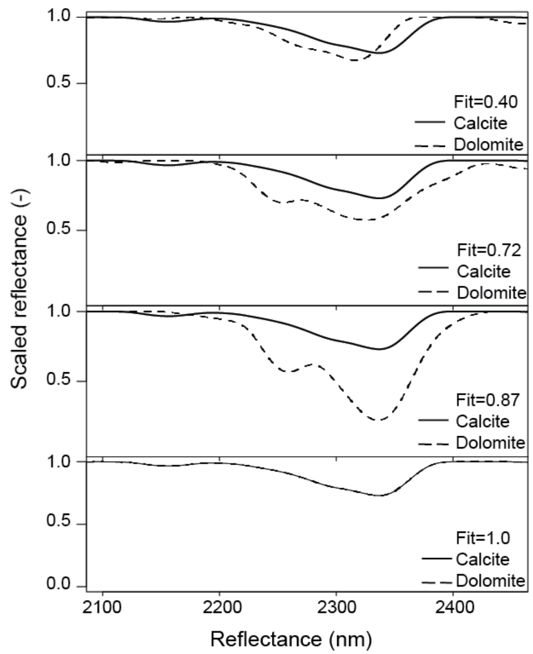


Problem: inference of mineralogy

1. Many minerals in a single sample
2. Absorption features not distinct

V.L. Mulder, S de Bruin, M.E. Schaepman, (2012). Retrieval of composite mineralogy by VNIR spectroscopy, 5th Global Workshop on Digital Soil Mapping 2012, Sydney, Australia.

Experiment 1: Mineral Identification & Classification Algorithm (MICA) USGS Processing Routines in IDL for Spectroscopic Measurements (PRISM)



Results

- Mineral categories
- Overall accuracy 52%

Mineral	Calcite-rich	Calcite-poor
Kaolinite	38	17
Smectite	6	27
Dioctahedral Mica	40	34

V.L. Mulder, S de Bruin, M.E. Schaepman, (2012). Retrieval of composite mineralogy by VNIR spectroscopy, 5th Global Workshop on Digital Soil Mapping 2012, Sydney, Australia.

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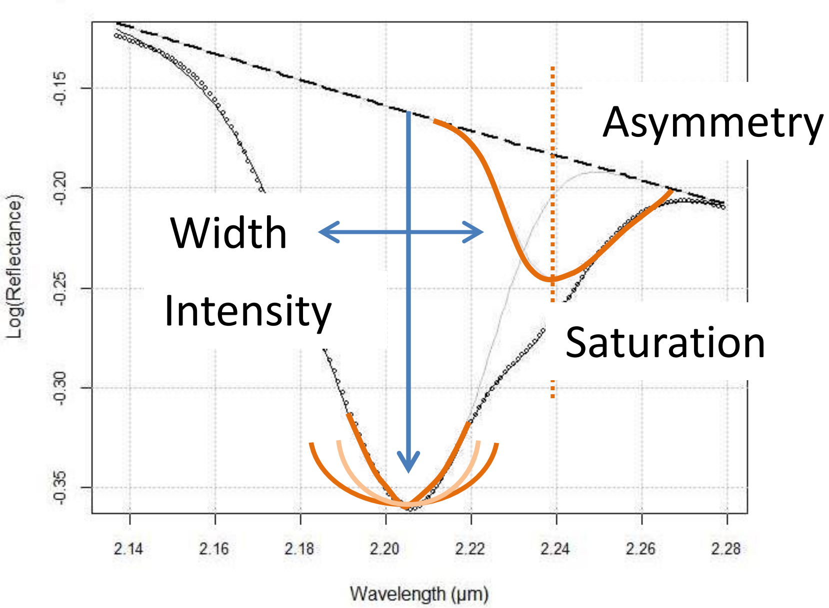
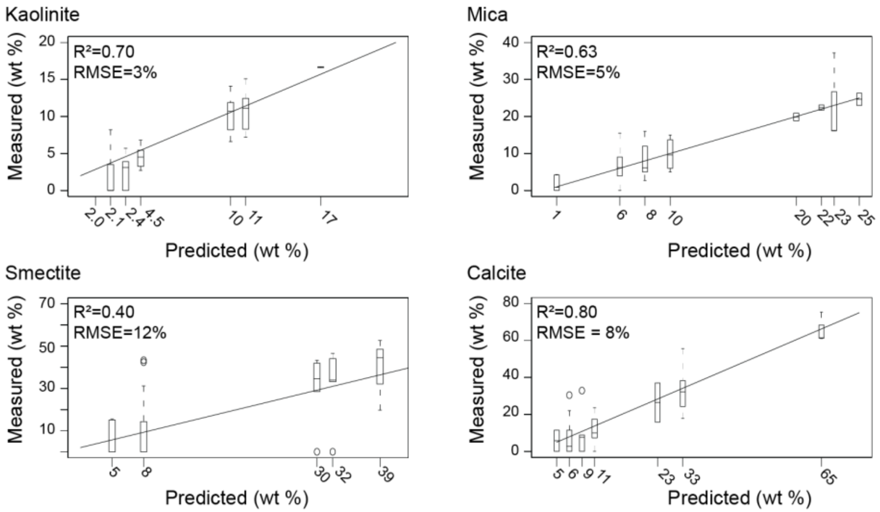
Spectral deconvolution coupled with regression tree analysis

Method



Results (natural samples)



V.L. Mulder, M. Plotze, S. de Bruin, S., M.E. Schaepman, C. Mavris, R. Kokaly, M. Egli, M., (2013). Quantifying mineral abundances of complex mixtures by coupling spectral deconvolution of SWIR spectra (2.1-2.4 µm) and regression tree analysis. Geoderma, (207) 279-290. DOI: 10.1016/j.geoderma.2013.05.011

Why?

- Remember: 100 samples
- Represent **major** variability
  - Very low spatial correlation
- RS data: high resolution – high variability
- Result: **few compatibility in variability**
- Smoothing – the RS data represent similar variability as the sampled soils

MAPPING

Can **scale-dependent variability** be extracted from **remote sensing** and do model predictions improve by using scaled remote sensing that **match** the variability of **the sample**?

Methods

- Fixed Rank Kriging (Cressie and Johannesson, 2008)
  - Handles large datasets
  - Interpolate gaps
  - Smoothing data based on medium and long-scale processes
- Model soil mineralogy
  1. Mineral categories & mineral abundances
  2. Predictor variables from satellite data
  - Statistical relation between 1 & 2

Cressie, N., Johannesson, G., 2008. Fixed rank kriging for very large spatial data sets. Journal of the Royal Statistical Society. Series B: Statistical Methodology 70(1), 209-226.

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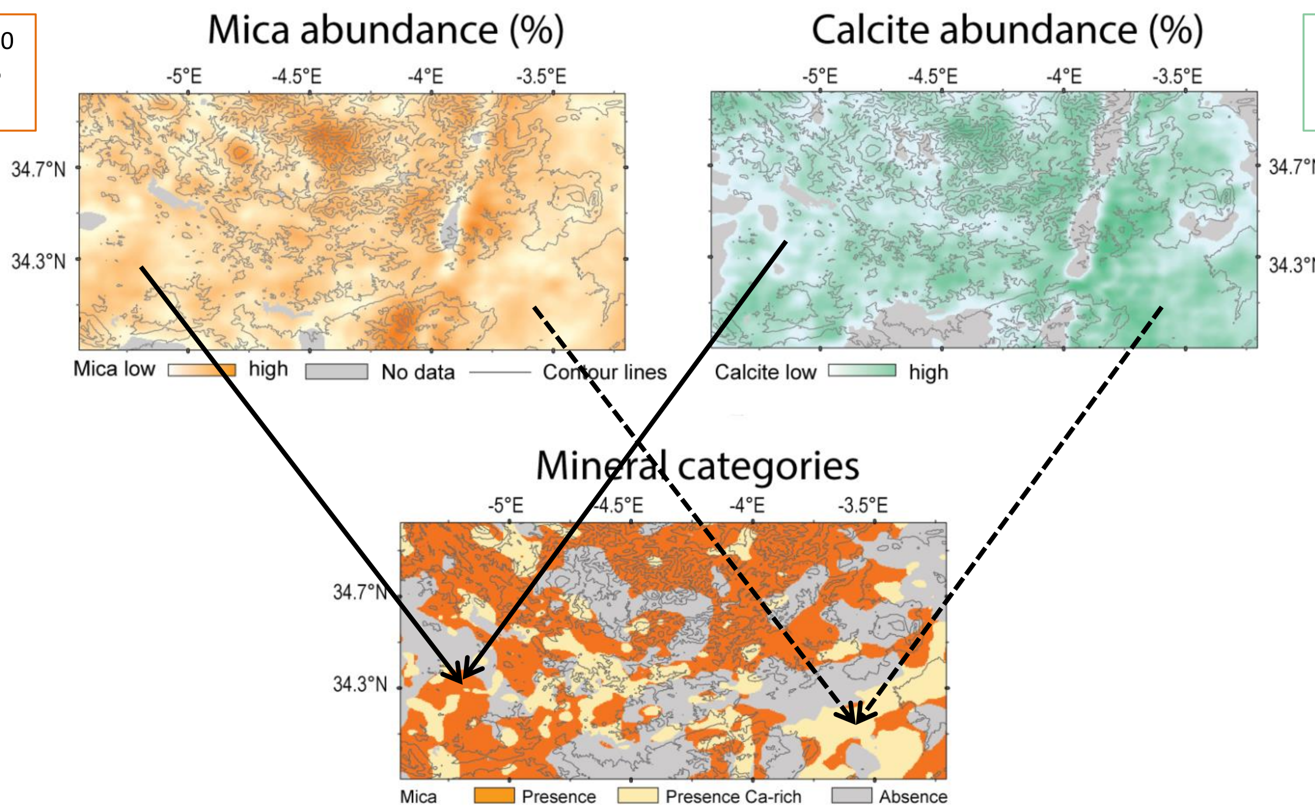
Characterizing regional soil mineralogy (II)

R_{adj}^2 = 0.70
$RMSE_{cal}$ = 4.6
$RMSE_{val}$ = 6

R_{adj}^2 = 0.71
$RMSE_{cal}$ = 8.9
$RMSE_{val}$ = 12



Overall accuracy 76%

V.L. Mulder, S. de Bruin, S., J. Weyermann, R. Kokaly, M.E. Schaepman, (2013). Characterizing regional soil mineral composition using spectroscopy and geostatistics. Remote Sensing of Environment (139),415-429. DOI: 10.1016/j.rse.2013.08.018

GENERAL CONCLUSION

Spectroscopy-supported digital soil mapping is **time** and **cost efficient** for large-scale soil assessments

Improvements in regional-scale DSM result from the **integrated use** of **remote sensing** with **geostatistical methods**

OUTLOOK

To deliver **accurate** and **comprehensive** information about **soils**, **soil resources** and **ecosystem services** provided by soils at regional and ultimately global scale

Essentially, all life depends upon the soil.
There can be no life without soil and no soil without life;
they have evolved together.

American naturalist Charles Kellogg, 1938.

Thank you all