

MOOC Document

Beyond the Visible – Imaging Spectroscopy for Soil Applications

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- 02** Pre-Assessment: Ready for hyperspectral applications?
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List of Abbreviations

The list includes all terms that are introduced in the MOOC.

AI: Artificial Intelligence	EeTeS: EnMAP end-to-end simulator
Al: Aluminum	EMIT: Earth surface Mineral dust source
API: Application Programming Interface	InvesTigation
ARES: Airborne Research Facility for the Earth System	EnMAP: Germany's Environmental Mapping and Analysis Program
ASD: Analytical Spectral Devices	EnSoMAP: EnMAP Soil Mapper
ASI: Italian Space Agency	ENVI: Environment for Visualizing Images software
ATB: Leibniz-Institut für Agrartechnik und Bioökonomie e.V.	ESA: European Space Agency
AVIRIS-NG: Airborne Visible Infrared Imaging Spectrometer – Next Generation	FAO: Food and Agriculture Organization of the United Nations
BRDF: Bidirectional Reflectance Distribution Function	Fe²⁺: Ferrous iron
BSSL: Brazilian soil spectral library	Fe³⁺: Ferric iron
C: Carbon	GFZ: German Research Center for Geosciences (Potsdam)
CEC: Cation exchange capacity	GIS: Geographic Information System
CHIME: ESA's Copernicus Hyperspectral Imaging Mission of the Environment	GLADA: Global Assessment of Land Degradation and Improvement
CO₃²⁻: Carbonate ion	GLASOD: Global Assessment of Human-induced soil degradation
CSSL: Chinese Soil Spectral Library	GPR: Gaussian process regression
DLR: German Space Agency	GSSL: GEO-CRADLE spectral library
DN: Digital number	HYSOMA: Hyperspectral Soil Mapper
EC: Electrical Conductivity	

ICRAF: International Council for Research in Agroforestry	PCA: Principal Component Analysis
ISRIC: International Soil Reference and Information Centre	PLSR: Partial-least squares regression
ISS: International Space Station	PRISMA: PRecursores IperSpettrale della Missione Applicativa
LADA: Land Degradation Assessment in Dryland	R²: Coefficient of determination
LMU: Ludwig-Maximilians-Universität München	RF: Random forest
LUCAS: Land Use/Land Cover Area Frame Survey	RI: Redness Index
Mg: Magnesium	RMSE: Root mean squared error
MIR: Mid infrared	RPD: Residual Predictive Deviation
MNF: Minimum Noise Fraction Transformation	SATVI: Soil-adjusted total vegetation index
MOOC: Massive open online course	SBG: NASA's Surface Biology and Geology Investigation Mission
N: Nitrogen	Si: Silicium
NASA: National Aeronautics and Space Administration	SOC: Soil organic Carbon
NDGI: Normalized difference gypsum index	SOM: Soil organic matter
NIR: Near-infrared	SVM: Support Vector Machine
NPV: Non-photosynthetic vegetation	SWIR: Short wave infrared
NSMI: Normalized Soil Moisture Index	SWIR FI: SWIR Fine Particulate Index
O: Oxygen	TIR: Thermal infrared
OH: Hydroxide ion	TOA: Top-of-Atmosphere
OSSL: Open Soil Spectral Library	UNCCD: United Nations Convention to Combat Desertification
	USGS: United States Geological Survey
	UV: Ultraviolet
	VIS: Visible (light)
	VNIR: Visible near-infrared

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1 Welcome

Hi there, welcome to the Massive Open Online Course (MOOC) ***„Beyond the Visible – Imaging Spectroscopy on Soil Applications“***!

This course is **structured in six lessons** that usually **contain several topics** and are accompanied as well as completed by a number of **short exercises** and **quizzes**.

The first lesson is accessible to everyone – here, you will meet your instructors and they will explain the benefits of hyperspectral over other types of remote sensing data and the challenges and opportunities for applications in a soil context. Plus, you can learn about [EnMAP](#), the German hyperspectral satellite mission that triggered the creation of this series of MOOCs! This lesson is not compulsory to pass the MOOC, but we hope that you find some valuable information relating to your area(s) of interest.

The second lesson is a quiz on the very basics of hyperspectral remote sensing that you need to pass in order to get access to the rest of the course – this is not to discourage you, but to ensure you have sufficient background knowledge to enjoy this MOOC. Don't worry, you have unlimited attempts to pass ...

The third, fourth, and fifth lessons contain the actual content and will introduce you to the (theoretical) background of soil reflectance, including which properties can be retrieved from hyperspectral imagery and how to collect reference data in the field, followed by some methodological considerations in a soil application context. In the final lesson, you'll get the chance to participate in two expert-led hands-on training exercises.

These „core“ thematic lessons (3-5) contain a lot of interactive content and you are requested to complete a short graded final quiz at the end of each lesson (10 questions each). In each final lesson-quiz (3) you need at least 50 % to pass to the next lesson. The course is completed by a final assessment, which includes a total of 15 questions. Here, you need at least 70 % to pass. If you have successfully done this, you will receive your certificate of completion as well as a diploma supplement! You have unlimited attempts to pass each quiz.

We use **the sixth lesson** to say goodbye – by then, you should have learned ...

- the benefits of imaging spectroscopy for soil applications
- the physical and chemical factors controlling soil reflectance (“chromophores”)

- which biophysical and biochemical properties can be retrieved as “soil variables”
- some basics of campaign- and sampling design
- how reference data are acquired in a soil context
- where you can get imaging spectroscopy data from and what software you could use
- which methods to apply in a soil context
- and finally, how to analyze an imaging spectroscopy dataset yourself!



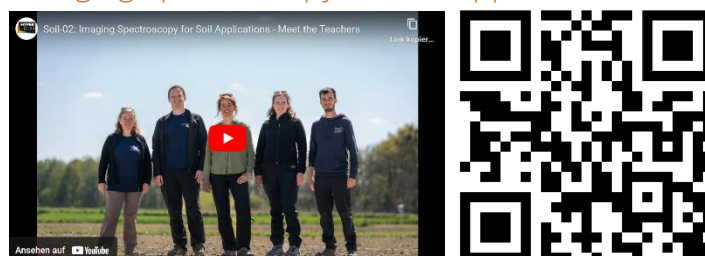
Advice – how to get through the course smoothly

This course was designed to be taken from a desktop PC or laptop, though most content should work on a tablet or even smartphone as well. For the best learning experience, we recommend participating using **Google Chrome**, **Microsoft Edge** or **Mozilla Firefox** on a **desktop PC** or **laptop**. During beta-testing, we observed some issues with Safari – if the content is not displayed properly, try re-loading.

If you prefer, you can use the **offline version of the course in PDF format**, which you will find under the resource section on EO-College. To complete the course and get the certificate, however, you still need to answer the quizzes in the online version of the course.

In the video you will be introduced to the institutions and colleagues who developed this course. You will meet them again throughout the course.

VIDEO: Soil-02: Imaging Spectroscopy for Soil Applications – Meet the Teachers



URL of the video: <https://youtu.be/rnkrkQHwgRA>

Let's move on with the first topic **“Hyperspectral remote sensing for soil monitoring”** – what are you waiting for? Let's go!

1.1 Hyperspectral remote sensing for soil monitoring

Soil (lat. solum, floor) is the uppermost layer of the Earth's surface, formed by the weathering of exposed rocks and minerals. Its formation is controlled by climate, living organisms, topography, soil parent material, period of formation, and geographical location (McBratney 2003). Soils are divided into different horizons of a few centimeters to several meters depth and consist of four major components with varying compositions: anorganic matter (minerals), organic matter, liquids and gaseous phases (Tarbuck and Lutgens 2009). **As soil formation is an extremely slow process, soil can be considered essentially as a non-renewable resource** (European Commission 2006).

Soils are the great reservoir for the chemical, physical and biological properties that **control life and biodiversity on Earth** (FAO 2015) and are crucial for the world's food security, economic prosperity and therefore, quality of human life. However, **soils worldwide are affected by degradation**. Driven by a variety of factors, land degradation leads to a reduction in soil productivity and biodiversity (Jones et al. 2012, Kosmas et al. 2014) and thus, to a decline in ecosystem services. According to the United Nations Convention to Combat Desertification (UNCCD) Global Land Outlook (2017), the steep increase in land degradation throughout the last decades is driven by eight main issues: soil erosion, the loss of soil organic carbon, the loss of soil biodiversity, salinization and sodification, contamination, acidification, compaction, and sealing. With regard to climate change, the degradation of soils leads to a release of carbon into the atmosphere and a decrease in soil fertility as well as productivity, thereby threatening food security. As the largest organic carbon pool worldwide, degrading soils can contribute considerably to climate change and its adverse impacts (Pimentel and Burgess 2013, COM 2012).

In the past decades, several "land assessments" attempted to evaluate natural or man-made soil degradation based on, among others, remote sensing information: The Food and Agriculture Organization of the United Nations (FAO) **GLASOD (1991)**, the **Millennium Assessment (MA 2005)**, the FAO's **GLADA (2008)**, and finally the FAO's **LADA (2010)**. Their results differed considerably, as they used either different data products and time series, soil degradation factors, or focused on different regions with varying scales on Earth. Consequently, they cannot be directly compared, leading to a still incomplete knowledge of the actual proportion of continental areas affected by land degradation on a global scale.

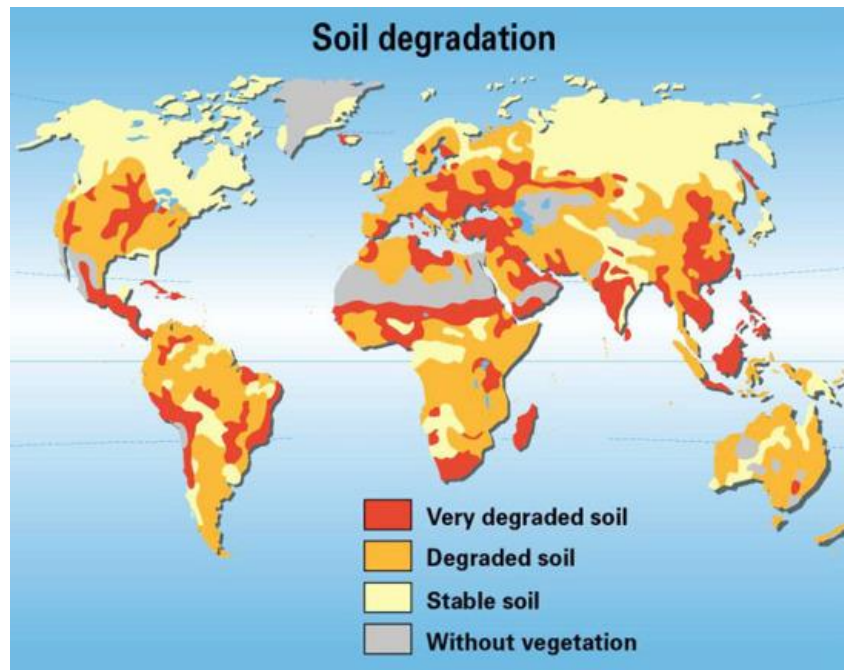


Figure 1 Soil Degradation.
Rekacewicz, P., UNEP/GRID-Arendal (2005)

The world's land surface is about 14,9 billion hectares (ha), of which about 5.1 billion ha are usable for agriculture (Ritchie and Roser 2013). Based on GLASOD (1991) estimates, 38 % (1.9 billion hectares) of the world's tropics and dryland zones are affected by irreversible degradation (Lal et al. 1997). Of the total land mass, about 15 % to 41 % is affected by land degradation, with negative impacts on up to 3.2 billion people worldwide (e.g. GLASOD 1991, GLO 2019). Fertile soil is being lost at rates of 24 billion to 75 billion tons per year (e.g. COM 2012). This all results in long-term food productivity being threatened by soil degradation (COM 2012), especially in view of a growing world population.

Environmental as well as sociopolitical problems resulting from land degradation are of trans-boundary nature and require attention on a global scale (Safriel 2007). There is a need for monitoring and mapping of soils and their processes for larger scales and with a higher temporal resolution – **currently available soil maps are often outdated and spatially not continuous on a global scale.**

Given the large size of the Earth's land mass and the number of countries involved in reaching consensus, large scale mapping can only realistically be accomplished with remote sensing data (Ustin and Middleton 2021). Thereby, imaging spectroscopy has been recognized as a cost-effective tool for the continuous large-scale assessment, mapping and monitoring of soil and soil erosion (Sivakumar and Ndiang'Ui 2007, COM 2012, Shoshany et al. 2013).

Today, a **new generation of spaceborne imaging spectroscopy missions** is underway, which will enable us to repetitively quantify important soil properties, including soil organic carbon, various soil contaminants, as well as acidification or salinization.



Why should we prefer hyperspectral sensors over multi – spectral systems?

Ustin and Middleton (2021) elaborated on this issue specifically for ecological applications:

“There is an unprecedented array of new satellite technologies with capabilities for advancing our understanding of ecological processes and the changing composition of the Earth’s biosphere at scales from local plots to the whole planet.”

“Hyperspectral (or spectroscopy-based) imagery allows identification of detailed chemical composition because the large number of bands, especially when they are narrow and contiguous or overlapping, can directly describe relevant absorption or reflectance features...”

“The capabilities of these next-generation technologies have the potential to bridge the existing data gaps and revolutionize our understanding of the magnitude and speed of change across global ecosystems, but significantly more research is needed on the rates of ecosystem structure and compositional change before this vision can be realized” (Ustin and Middleton 2021). For our MOOC “Beyond the Visible – Introduction to Hyperspectral Remote Sensing” **Prof. Dr. Sabine Chabrillat** (Leibniz University Hannover and GFZ German Research Centre for GeoSciences in Potsdam) summarized the **advantages and current challenges of hyperspectral remote sensing in the context of soil applications** in an **interview**:

VIDEO: Basic-02: Expert interview: application field “soils and geology”



URL of the video: <https://youtu.be/g6zSSjBK1Vk>



Let us and your fellow students know who you are, what question(s) you are interested in, and for which research question you would like to use hyperspectral data in the **discussion forum** of this topic. There is a separate discussion forum for each topic of this course in the **discussion section at EO-College**.

1.2 EnMAP – The German Spaceborne Imaging Spectroscopy Mission

The **Environmental Mapping and Analysis Program (EnMAP)** is a German **hyperspectral satellite mission** that aims to monitor and characterize Earth's environment by utilizing its regional coverage on a global scale. EnMAP measures and models key ecosystem processes by extracting geochemical, biochemical and biophysical parameters that provide information on the status and evolution of various terrestrial and aquatic ecosystems. It is funded under the German Space Agency at DLR with resources from the German Federal Ministry for Economic Affairs and Climate Action. The mission is accompanied by an extensive scientific preparation program and educational initiative. In this context, we have developed an open source software (EnMAP-Box) and trained a number of experts in the past decade. This MOOC is the next step to sharing our knowledge with all potential users of hyperspectral data and encouraging the growth of a global imaging spectroscopy community.

VIDEO: Basic-05: Sensor technologies & data acquisition techniques: EnMAP Mission



URL of the video: <https://youtu.be/LQZNtLp3RfM>

1.3 Resources section: 'Hyperspectral remote sensing for soil monitoring'

In this section, we have assembled resources used for the creation of this lesson that we recommend for further reading as they provide a lot more detail. Please remember that this selection is not a complete overview of all resources – if you think an important resource is missing, let us and your fellow students know (e.g. in the discussion forum).



Sources and further reading

State-of-the-Art Publications

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Topic 1.2: EnMAP – The German Spaceborne Imaging Spectroscopy Mission

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2 Pre-assessment: Ready for hyperspectral applications?

Are you ready for the application of imaging spectroscopy data? As mentioned before, in order to really enjoy this course, **you should have some basic understanding of hyperspectral remote sensing principles**. If you pass the following quiz, you are very welcome to continue. If you don't score the required minimum (7 out of 10 correct answers, 70 %), then we recommend that you look into some more basic resources before taking this course, e.g. our basic MOOC '[Beyond the Visible: Introduction to Imaging Spectroscopy](#)'. Anyway, you have **unlimited attempts to pass the quiz**. Here we go and good luck!

2.1 Pre-Assessment Quiz

An object will appear red to the observer ... (single-choice)

- ... if it absorbs only red wavelengths
- ... if it transmits only red wavelengths
- ... if it reflects all visible wavelengths equally
- ... if it mostly reflects red wavelengths

Sort the wavelength ranges from short to long wavelengths

Choose an element

Choose an element

Choose an element

Choose an element

Choose an element

Choose an element

Choose an element

Which parts of the electromagnetic spectrum can we see? (single-choice)

- Ultraviolet light
- Visible light
- Infrared light
- Microwaves

The spectral region where electromagnetic radiation passes through the atmosphere without much attenuation is known as ... (single-choice)

- ... ozone hole
- ... atmospheric window
- ... black hole
- ... skylight

Can you identify some advantages of imaging spectroscopy data? (multiple-choice)

- The data contains a high level of spectral detail
- The data allow for the retrieval of a range of different surface variables
- Analysis is much faster and easier compared to other types of remote sensing data

What is a radiometric correction and what does it do? (multiple-choice)

- It transforms digital numbers to radiance
- It transforms digital numbers to reflectance
- It involves data resampling using nearest neighbor, bilinear interpolation or cubic convolution methods
- It involves a linear transformation in which correction coefficients (gain and offset) are applied to every image pixel

Which surface material has usually the lowest reflectance in the SWIR? (single-choice)

- Clear water
- Green vegetation
- Dry vegetation
- Open soil

Which factors influence the reflectance of vegetation? (multiple-choice)

- Moisture content
- Species
- Phenology
- Health

Healthy vegetation strongly reflects light in which parts of the electromagnetic spectrum? (single-choice)

- Green and red
- Blue and green
- Green and near-infrared
- Blue and red

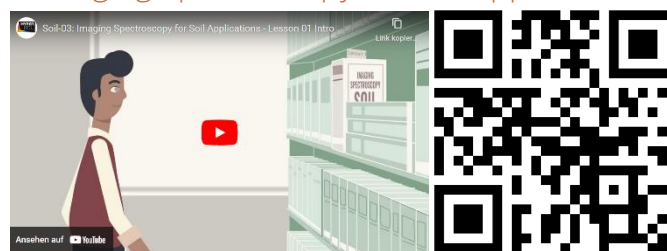
What is a Lambertian surface? (single-choice)

- An ideal specular reflector
- An ideal diffuse reflector
- A calibration target
- A perfect emitter

3 Introduction to imaging spectroscopy for soil applications

In this lesson, we want to introduce you to the principles of **imaging spectroscopy for soil applications** – Charly will give you more details on the specific learning objectives in the video below!

VIDEO: Soil-03: Imaging Spectroscopy for Soil Applications – Lesson 01 Intro



URL of the video: <https://youtu.be/G-V-aZkTQ9M>

Let's move on with the first topic of this lesson!

3.1 Imaging Spectroscopy of soil

As electromagnetic **radiation** hits a surface, it is **partly reflected, absorbed and/or transmitted**. Thereby, the fractions of absorbed, transmitted and/or reflected radiation vary depending on material and wavelength. Remember? This is the basis for remote sensing!

The radiation penetrating the **leaf** is subject to numerous processes like **absorption** by leaf pigments in chloroplasts, cell water and other leaf constituents. Leaves are radiation receivers: approximately 80 – 90% of the absorbed radiation occurs in the leaves! In addition, **multiple scattering and refraction** occur on the cell walls within the cells, at chloroplasts and other cell organelles and especially in the air-filled intercellular spaces.

$$\text{Irradiance (I)} = \text{Absorption (A)} + \text{Transmission (T)} + \text{Reflectance (R)}$$

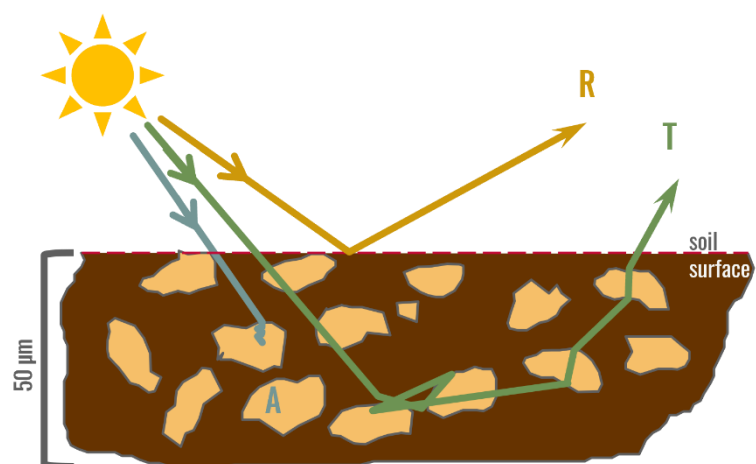


Figure 2 Interaction of radiance with soil.
In courtesy of Hermann Kaufmann

For most imaging spectroscopy applications, the goal is to retrieve the spectral response (L_t) of soil surfaces (L_s) and the subsurface related to transmission and volume scattering (L_v). Therefore, atmospheric correction is essential to separate the soil signal from atmospheric attenuation (L_p). As the volume scattering within the soil often occurs as multiple scattering, the process is not necessarily linear! Imaging spectroscopy (or optical remote sensing) of soil in general is, however, limited to the penetration depth of energy in the optical domain! Thus, approximately only the uppermost 50 μm is visible to the sensors (penetration depth: $\lambda / 2$).

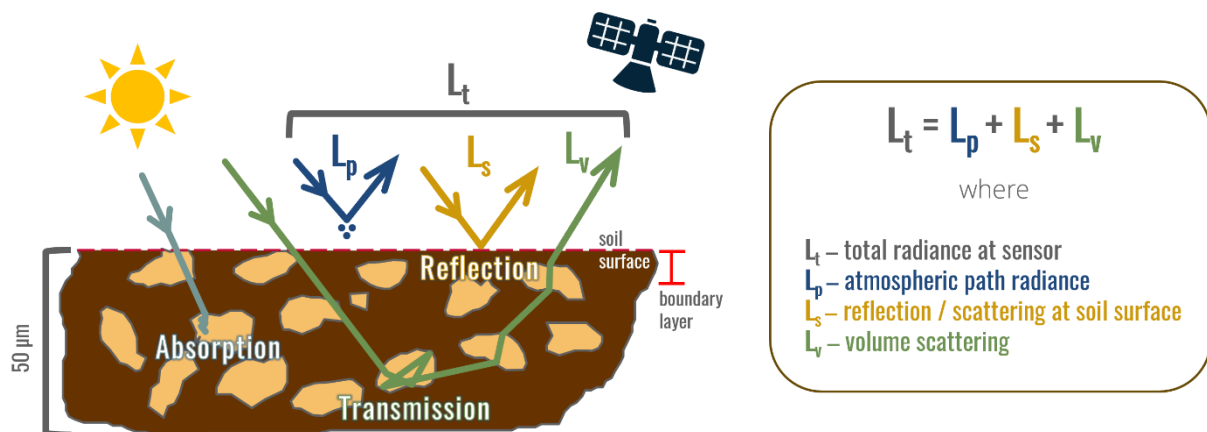


Figure 3 Interaction of radiance with soil from sensor perspective.
In courtesy of Hermann Kaufmann

As with all other materials, radiant energy arriving at the soil stimulates electron transfer (to higher energy levels) and vibrational processes (stretching, rotational and deformation oscillations) at the molecular level. Detailed descriptions of these processes can be found e.g. in Hunt (1977) and Clark (1999). In short, energy is extracted from the incoming radiation and released when the process relaxes. This energy is used for processes of material conversion and leads to the heating of the soil, resulting in the emission of long-wave radiation. Since only discrete electron levels can occur in atoms and the excitation of oscillation processes is only possible by photons with a certain energy, a certain wavelength can be assigned to each absorption process. For visualization of the outcome, check the figure below!

As electron transfer processes require a lot of energy, the bands caused by them are usually quite broad and in the short-wave UV range, partly with absorption minima extending into the visual range (e.g. iron oxides). Vibrational processes cause rather narrow bands in the SWIR range as their excitation requires less energy. In practice, this means that in addition to more general effects, some soil constituents cause very specific absorption features that allow for their identification and quantification. The major constituents of soil minerals (O, Si, Al, and Mg) do not exhibit absorption features in the VNIR and SWIR range (Hunt 1977), they are located in the thermal infrared. In the VNIR and SWIR, absorption bands are due to combinations or

overtones of the fundamentals. The resulting VNIR-SWIR **spectral reflectance characteristics are mainly influenced by mineralogical composition (such as organic matter content, clay content and soil texture, iron-oxide content, carbonates, salinity) and by moisture content and surface roughness** – you will find more in-depth information on this in the upcoming lesson. Typically, soils have broad and shallow absorption features at wavelengths between 400 nm and 2500 nm, that are related to iron oxide and organic matter. In general, reflectance decreases with increasing organic matter and/or moisture content. Increases in particle size also cause a decrease in overall reflectance. Even small amounts of iron oxides can alter VNIR spectra significantly, causing broad absorption features particularly around 400 nm, 700 nm and 870 nm (Ben-Dor et al. 1999). In contrast, several clay minerals (e.g., montmorillonite, kaolinite, illite, smectite) and carbonates display distinctive narrow-band absorption features in the SWIR range between 2000 nm and 2500 nm (Ustin et al. 2004). In addition, there are **multiple scattering processes**, which determine the shape of the absorption bands.

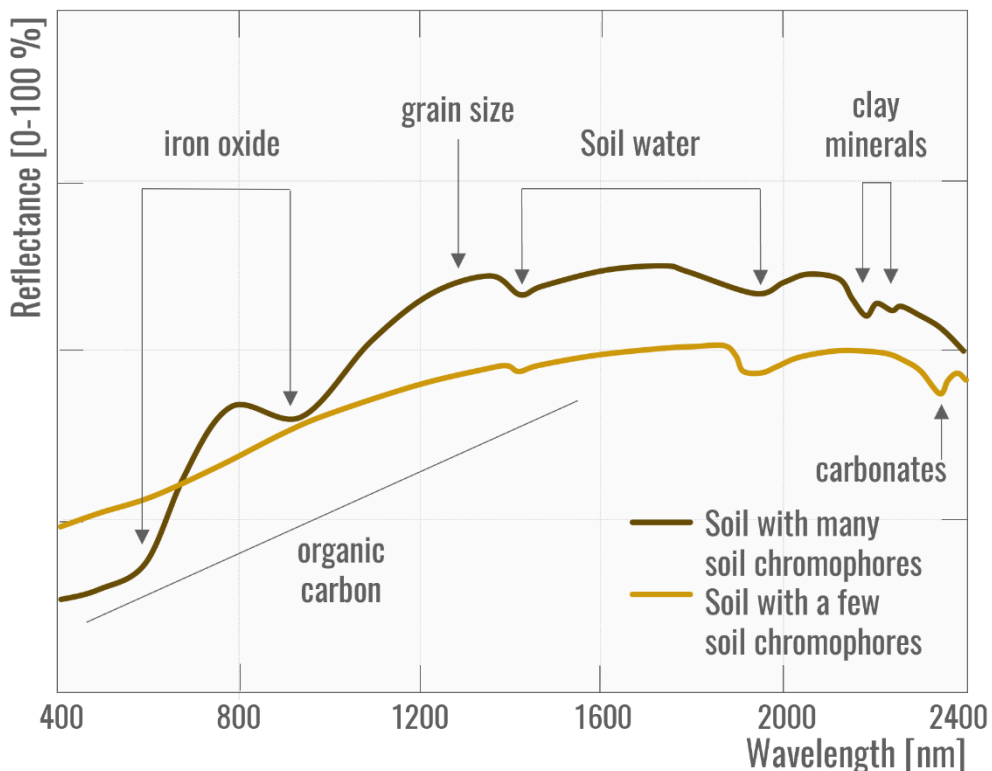


Figure 4 Soil spectral characteristics.
Spectra in courtesy of Sabine Chabrillat and Robert Milewski

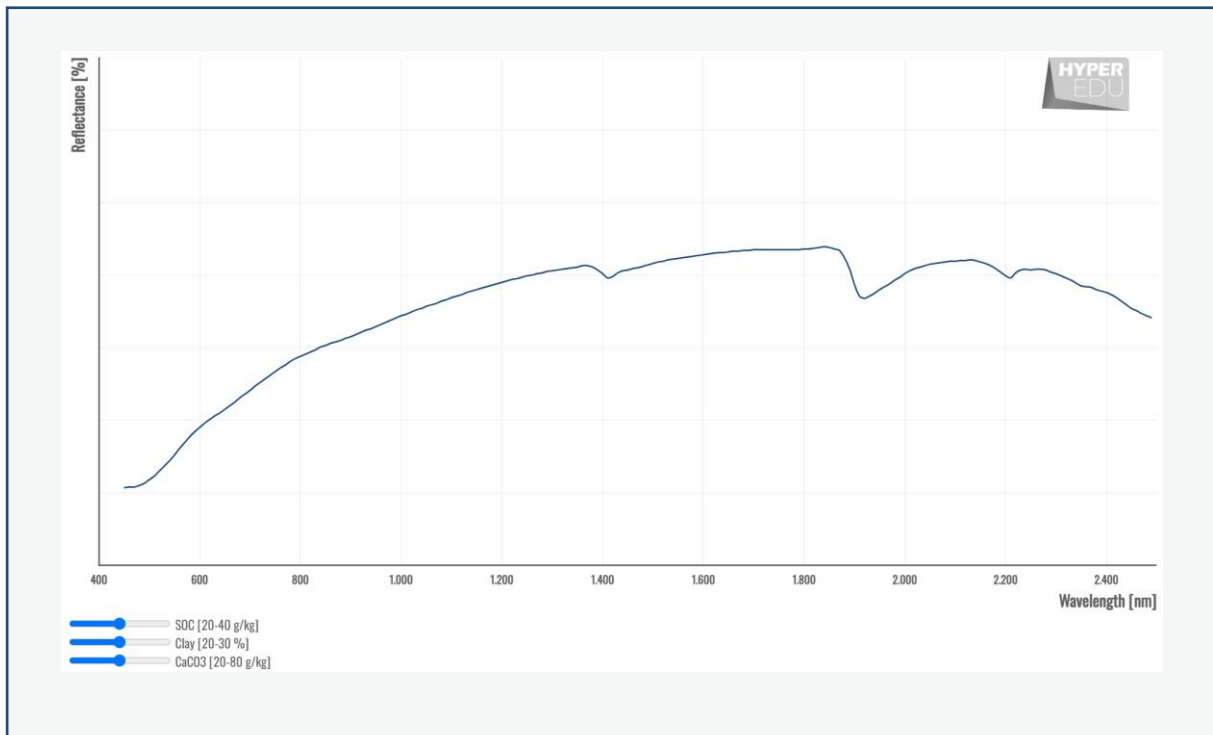


Interactive graphic – Explore the spectral reflectance of soils – Available under this [Link](#)

In the [interactive graphic](#) below, you can manipulate some parameters, namely soil organic carbon (SOC) content, clay content and carbonate content (CaCO_3). As you move the sliders, the contents increase or decrease (values indicated in brackets) and the spectrum adapts accordingly.

Unlike the (similar) interactive graphic on vegetation that you might be familiar with from our other MOOCs, this graphic is *not* based on simulated spectra but on averaged spectra from the European LUCAS soil spectral library (SSL) 2009/12. The subset of data used to create this graphic consisted of 11273 soil spectra originating from croplands, grasslands and forests within Europe. Each spectrum shown is an average of all spectra in the subset within a defined soil property range (as indicated with the sliders). Please consider that the number of samples per soil property range is *not* distributed equally, especially for higher soil property ranges. There are some combinations of properties that are rather rare or do not exist at all in (European) soils and for which, thus, no spectra can be displayed in the graphic (e.g. the combination max. SOC, CaCO_3 80-200 g/kg and variable clay content). Besides, you can observe the effects of variable albedo (“brightness”) or of other soil properties (like iron oxide) not in the focus of this graphic.

In summary, the averaged spectra are representatives of soil reflectance for a certain range of properties in European soils and certainly do not represent average soil property contents, considering e.g. data skewness or also the variability of soils and soil properties in other parts of the world! However, when manipulating the sliders, you can nicely observe the general changes of spectral features that are caused by the changes in soil property contents, especially if you set the other properties to low values.



By the way, **in order to differentiate between bare soil and dry vegetation, also called NPV for non-photosynthetic vegetation (such as residues at the crop surfaces), hyperspectral information is crucial**, as these two land cover types can only be distinguished using the cellulose absorption feature around 2100 nm.

By now, you should be familiar with the spectral reflectance properties of vegetation. Come on and test your knowledge by assigning the terms to the spectra below:

Quiz: Imaging spectroscopy of soil

Fill in the blanks

In general, reflectance **Choose an element** with **Choose an element** organic matter and/or moisture content. Increases in particle size also cause a **Choose an element** in overall reflectance.

Since the major constituents of soil minerals (O, Si, Al, and Mg) do not exhibit absorption features in the VNIR and SWIR range, soil spectral reflectance characteristics are mainly influenced by ...(multiple-choice)

- ... iron-oxide content
- ... clay mineral composition
- ... organic matter content
- ... texture and surface roughness
- ... salinity
- ... moisture content
- ... dry vegetation residues

Dry vegetation and bare soil can be distinguished best based on...(single-choice)

- ... the cellulose absorption feature around 2100 nm
- ... the cellulose absorption feature between 700 and 1300 nm
- ... their water content

Even small amounts of Iron oxides can alter VNIR spectra significantly, causing broad absorption features particularly around...(single-choice)

- ...400 nm
- ...400 nm, 700 nm and 870 nm
- ...1400nm and 1700 nm
- ...2100 nm

3.2 Geophysical and geochemical variables

“A chromophore is a parameter or substance [...] that significantly affects the shape and nature of a soil spectrum” (Ben-Dor et al. 1999).

In general, substances that absorb energy in the VNIR-SWIR spectral region are considered **chemical chromophores**. Chemical chromophores are caused by charge transfer or electron transfer of ions (VNIR) and vibrational processes of chemical bonds (VNIR-SWIR). All circumstances governing the shape of a soil spectrum (e.g. slope and albedo) are considered **physical chromophores**, particularly internal scattering and surface roughness.

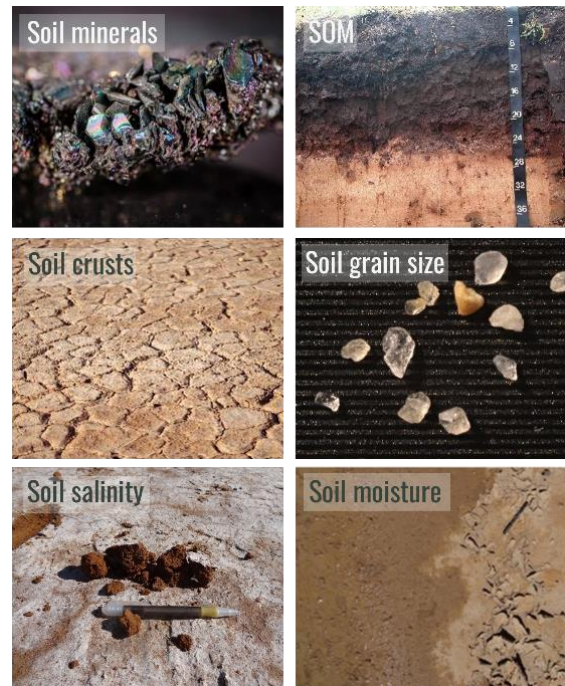


Figure 5 Essential soil chromophores. Images reprinted from Unsplash & Flickr; Photos in courtesy of Robert Milewski

The most essential and prominent soil chromophores are:

- Soil minerals
- Soil organic matter (SOM)
- Soil crusts
- Soil salinity
- Soil grain size
- Soil moisture

Soil chemical chromophores

In very general terms, soil is composed of approximately 45 % inorganic material (i.e. minerals of the particle size fractions sand, silt and clay), 5 to 15 % organic matter and up to 50 % pore space (containing different amounts of soil gases and water over time and space).

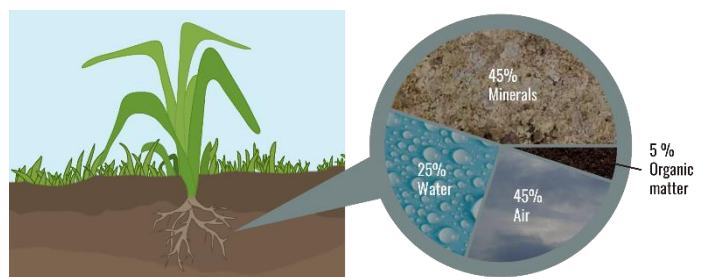
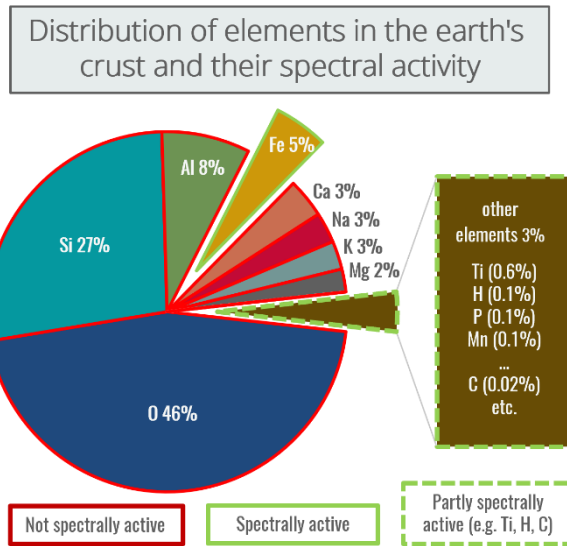


Figure 6 General soil composition. Based on numbers by Ben-Dor et al. (1999 and 2018)

Most of the abundant elements in the earth’s crust (e.g. O, Si, Al or Mg) are not spectrally active. They do not absorb energy in the VNIR-SWIR spectral ranges and thus do not alter the spectra in these wavelengths.



Then why are soils spectrally active? Well, spectral activity is expressed on the **molecular level** (Iron oxides, H₂O, OH⁻, SO₄²⁻, CO₃²⁻ or CH) and **not** on the **atomic level**. In addition, the soil spectral behavior can be modified by **indirect chromophores** that are correlated to spectrally active **direct chromophores**. The major chemical chromophores are:

Figure 7 Distribution of elements in the earth’s crust and their spectral activity.

Based on numbers in Tarbuck et al. (2009)

- **Soil minerals** (phyllosilicates, most sorosilicates, oxides (e.g., iron), hydroxides, some sulfates (gypsum), amphibols and carbonates)
- **Soil organic matter (SOM)**
- **Soil salinity**
- **Soil crusts**
- **Soil water** (considered both, a chemical **AND** a physical chromophore!)

Soil minerals (I): iron oxides

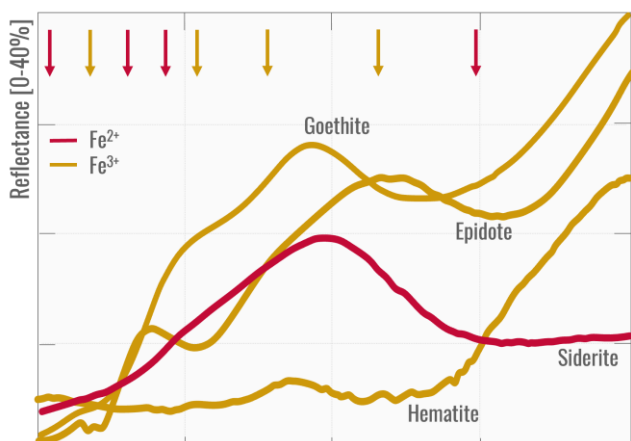


Figure 8 Chemical chromophores of iron oxide minerals. Spectra source USGS spectral library

Soil iron-oxide content can be an indicator of soil fertility, age and weathering conditions. Iron-rich soils show a strong reflectance decrease towards blue and UV spectral regions. Due to crystal field effects, ferrous iron (Fe²⁺) produces features around 410 nm, 450 nm, 510 nm, 550 nm and 1000 nm (Hunt 1971). Ferric iron (Fe³⁺) can produce features in the UV toward the VIS,

and at 470 nm, 700 nm and 870 nm due to electron exchange between ions (Hunt 1977).

Soil minerals (II): carbonates

Carbonates (i.e. calcite, dolomite) are found in soils formed from carbonic parent materials or a chemical environment that permits calcite and dolomite precipitation. The C-O bond of the carbonate ion (CO_3^{2-}) is the spectrally active chromophore. A major feature of carbonates occurs around 2300 nm, while the wavelength of the absorption center depends on the chemical composition. Further features occur in the SWIR spectral region as a result of overtones and combination modes around 1725 nm, 1860 nm, 1975 nm and 2135 nm.

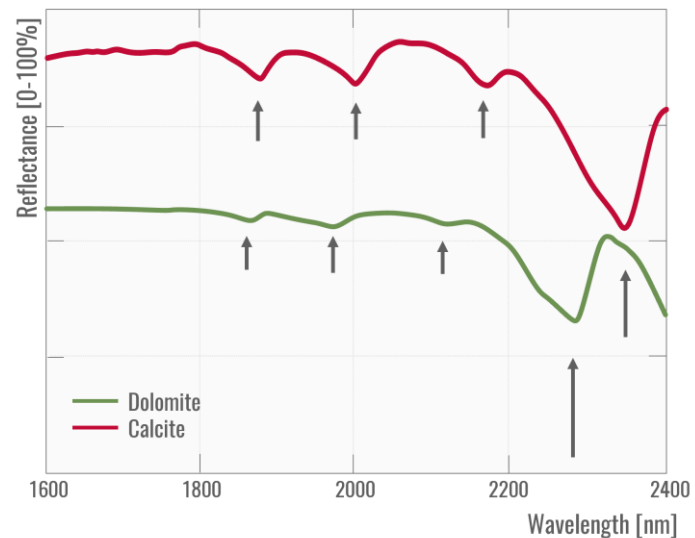


Figure 9 Chemical chromophores of carbonate minerals.
Spectra source USGS spectral library

Soil minerals (III): clay minerals

The spectrally active chemical chromophore of clay minerals is the hydroxide ion (OH^-) (Hunt 1979). The OH^- group of clays occurs as lattice water in the mineral structure and as adsorbed water on the mineral surface. Depending on the occurrence of the ion, the OH^- groups of clay minerals are active in the spectral regions 1300 -1400, 1800 - 1900 and / or 2200 - 2500 nm. Please note **that this information is about the chemical clay mineral group and not about the clay-sized grain fraction!** They are essentially **NOT** the same.

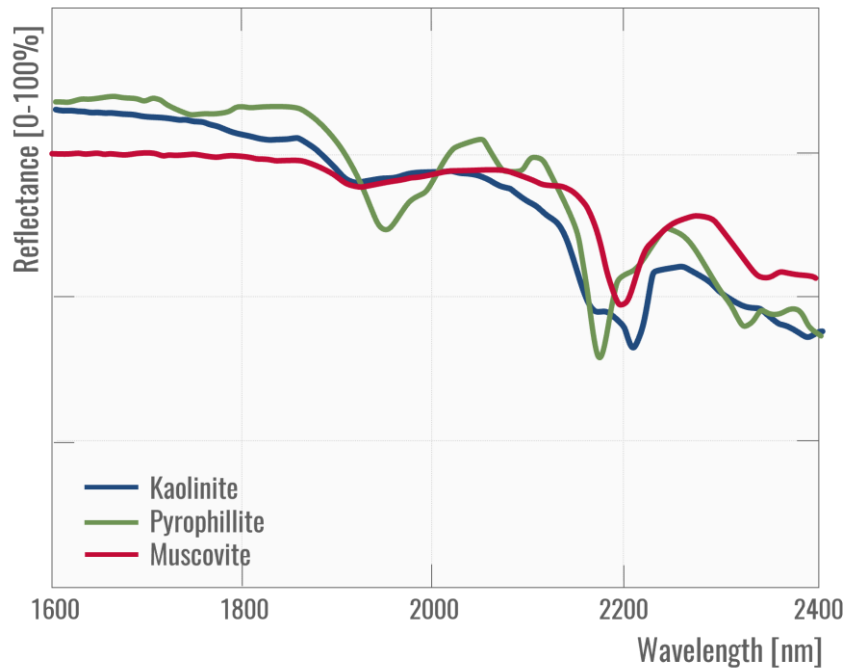


Figure 10 Chemical chromophores of various clay minerals.
Spectra source USGS spectral library

Soil minerals (IV): sulfate

Unlike many evaporite minerals (e.g. halite), gypsum and other sulfate-hydrates are active with multiple absorption features in the VNIR and SWIR spectral regions (Milewski et al. 2019). Due to hydration water built in the mineral lattice of gypsum, strong water absorption features occur at 1400 nm and 1900 nm (Hunt et al. 1971 and Ben-Dor et al. 1999). Diagnostic absorption bands are located at 1750 nm and around 2200 nm, with minor absorptions at 1000 nm and 1200 nm.

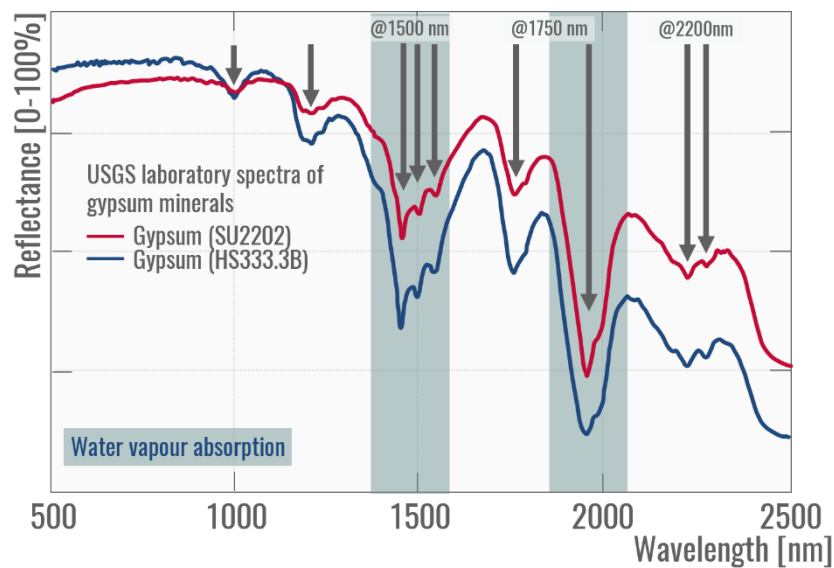


Figure 11 Chemical chromophores of sulfate minerals.
Adapted from Milewski et al. (2019)

Soil organic matter (SOM)

Soil organic matter (SOM) includes **all organic constituents in various stages of decomposition** (dead plants, animals and soil organisms, organic material < 2 mm) (Lefèvre et al. 2017). Soil organic matter exerts an **overall strong influence on soil reflectance characteristics throughout VNIR-SWIR region** (Pu 2017). Actually, **soil color** is a SOM indicator: the higher the SOM content, the lower the VIS reflection (i.e. the darker the soil). The main chromophores of SOM are humic acids and soil moisture (Mulder et al. 2011). Absorption bands in the VIS range are caused by charge transfer of chlorophyll, while absorption bands in the SWIR are caused by overtone and combination modes of N- and C-groups (many features related to starch, cellulose, lignin and water). Despite exerting a strong influence on soil spectral characteristics, soil organic matter is a tricky constituent: The spectral characteristics differ depending on the degree of decomposition and are strongly correlated with soil texture and clay content, making **robust quantification difficult**. SOM is composed of approx. 58% carbon, which is the SOC content (Blume et al. 2022) and a factor of 1.72 can be applied to transform SOC to SOM (Blume et al. 2002, Stenberg et al. 2010). Besides, from a content of 3 – 10%, **SOM can mask other soil characteristics!**

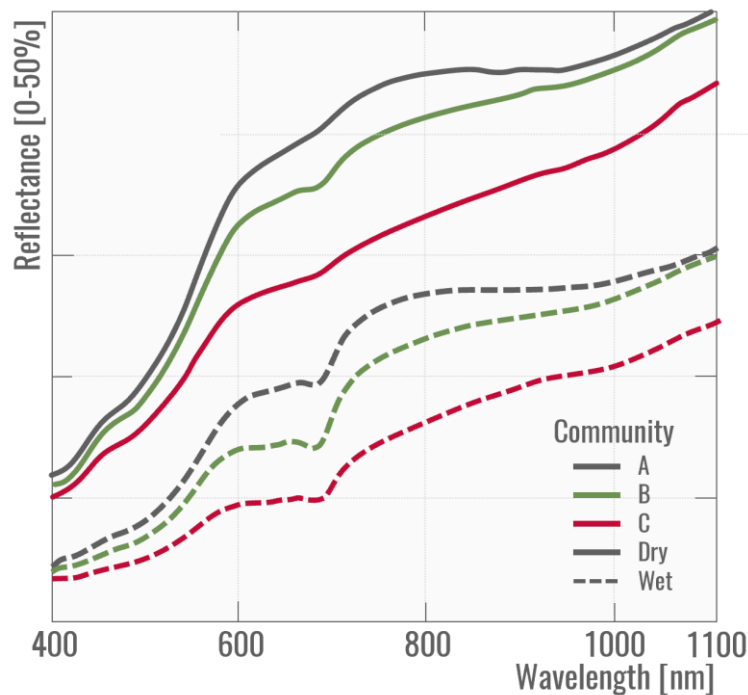


Figure 12 Spectral response of different microphytic communities (A, B, C) under different moisture conditions: dry samples and samples after wetting and 7 days of incubation. Note that the spectral signals decrease from community A to C.
Spectra in courtesy of Arnon Karnieli

Soil salinity

Soil salinity is a major cause for soil degradation (Ben-Dor 1999). Common salts in soils are Na_2CO_3 , NaHCO_3 and NaCl . Saline soils can exhibit distinct absorption bands in the entire VNIR-SWIR wavelength range. Highly salinized soils can exhibit features at 680 nm, 1180 nm and 1780 nm (Mulder et al. 2011). However, this is due to water in hydrated evaporite minerals that may accumulate in the saline milieu. Therefore, these absorptions should be considered as proxies for saline soils. As Mulder et al. (2011) pointed out, spectra of pure salt crystals do not otherwise show any measurable absorption characteristics and thus, saline soils are often without any features. Still, salts interact with other soil properties, which then indirectly influence soil reflectance (Ben-Dor and Demattê 2015). For example, rising salt concentrations in a soil can increase its electrical conductivity (EC). A side effect of that increased salinity can also be the formation of a salt crust on the soil surface due to evapotranspiration, which in turn leads to an increase in surface reflectance, as albedo increases (Ben-Dor and Demattê 2015).

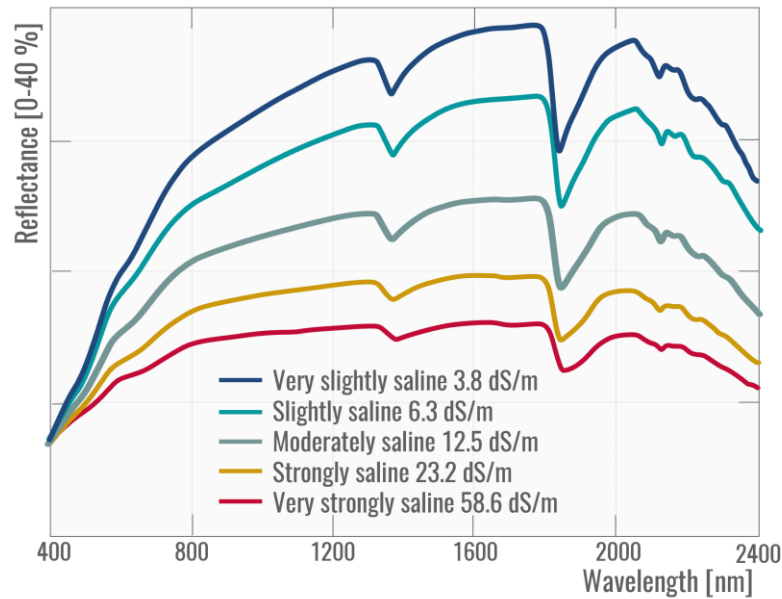


Figure 13 Reflectance spectra of five soil salinity classes. Redrawn from Nawar et al. (2014)

Soil crusts

The spectral behavior of the soil top layer can differ considerably from the underlying soil matrix (Chabrillat et al. 2019). This can be due to **biogenic crusts** (VIS region) caused by mosses, lichens, algae, fungi, cyanobacteria and bacteria and/or **mechanical/physical crusts** such as grain size segregation by wind and rain (e.g. formation of a „rain crust“ in humid climates and a desert varnish in arid climates), hydrothermal alteration or parent material formation due to weathering. Note: **Crusts can mask the spectral properties of soils!**

Soil water

Soil water is one of the most significant chromophores in soils and, as previously mentioned, is classified both as chemical and physical chromophore (Ben-Dor et al. 2009). In general, with increasing water content the soil reflectance decreases. The absorption features around 1400 nm and 1900 nm wavelength ranges become deeper and wider and the soil features e.g. here at 2200 nm (related to clay

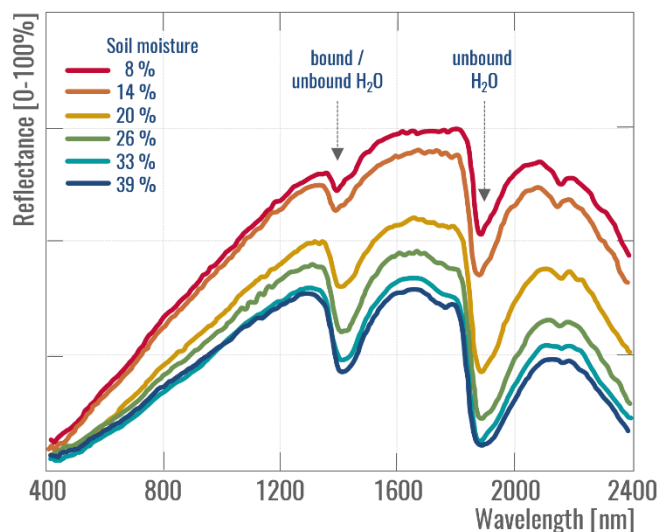


Figure 14 Chemical and physical chromophores of soil water. Spectra in courtesy of Heike Bach, VISTA

content) decrease. More specifically, there are three manifestations of water in soil:

- **Hydration water** shows strong features around 1400 nm, 1900 nm and a weaker feature around 2200 nm
- **Adsorbed hygroscopic water** strongly affects the water absorption bands at 1400 nm and 1900 nm and less at 950 nm and 1200 nm
- **Free water (H₂O)** in soil pores causes a strong albedo decrease as well as an amplification of the water features described above.

In-depth information on the behavior of soils with increasing water content are given, amongst others, in Ben-Dor et al. (2018).

Summary of soil chemical chromophores

The figure below presents a summary of soil chromophores in the VNIR and SWIR spectral range and associated intensities of absorption features. As you can see, the VNIR is dominated by crystal field effects as well as charge transfers of metal-ions. Vibration-related absorption features are mostly found in the SWIR. Soil spectral properties are strongly correlated with chromophores related to primary and secondary minerals, metal-oxides, organic matter, salts and water. Using high-resolution spectral data, these features can be utilized to derive quantitative information.

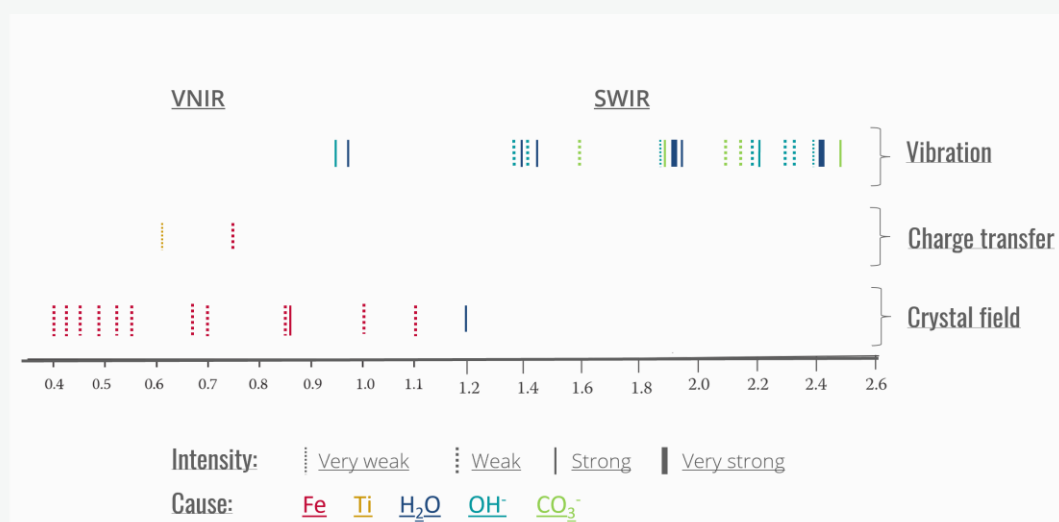


Figure 15 Summary of absorption features caused by chemical chromophores described above. Adapted from Ben-Dor and Demattê (2015)

Soil physical chromophores

Physical chromophores influence the shape of a spectrum by affecting the intensities of absorptions and the albedo (Ben-Dor 1999). They include:

- Soil particle size (sand, silt, clay fraction)
- Soil water
- Surface roughness (sample geometry)
- Viewing geometry

Soil particle size

Soil grain or aggregate size determines soil texture and surface roughness and therefore, has a major impact on the soil spectra. Consequently, **soil texture** is the function of sand/silt/clay distribution within the soil (Thenkabail 2018).

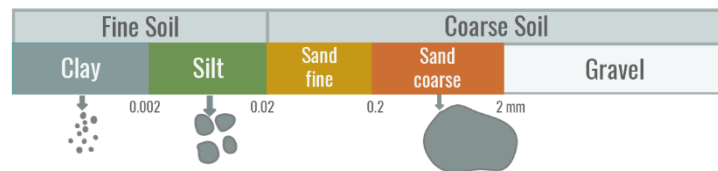


Figure 16 Soil texture classification.
Adapted from IUSS (1929)

Soil structure on the other hand is a function of adhesive forces between particles and describes the aggregation characteristics of a soil (Thenkabail 2018). **Very fine soils** tend to form compactions (> 2 mm) resulting in an increased roughness of the soil surface. Thus, they may **show** a similar or even more pronounced spectral behavior as coarse-grained soils (Richter 2010). In general, **albedo decreases with increasing grain size and vice versa**, especially between 1700 nm and 2200 nm. Closely related to the grain size distribution is the **physical soil water chromophore**. With decreasing grain size, soils show an increasing water storage capacity. Clays have a higher water retention potential compared to soils with larger grain sizes and hence, appear „darker“ than sandy soils when wet. However, in dry conditions, clayey soils show a higher base reflectivity (brighter) than soils with larger grain sizes (sandy soils).

Soil surface roughness

Soil roughness determines the proportion of micro shades on the soil surface and thus affects the soil's albedo. It is greatly influenced by soil aggregate size and the wavelengths of incident light. Irregularities of the surface > 2 μm appear as “rough” at VNIR-SWIR wavelengths. In general, **soil reflectivity decreases with increasing soil surface roughness**.

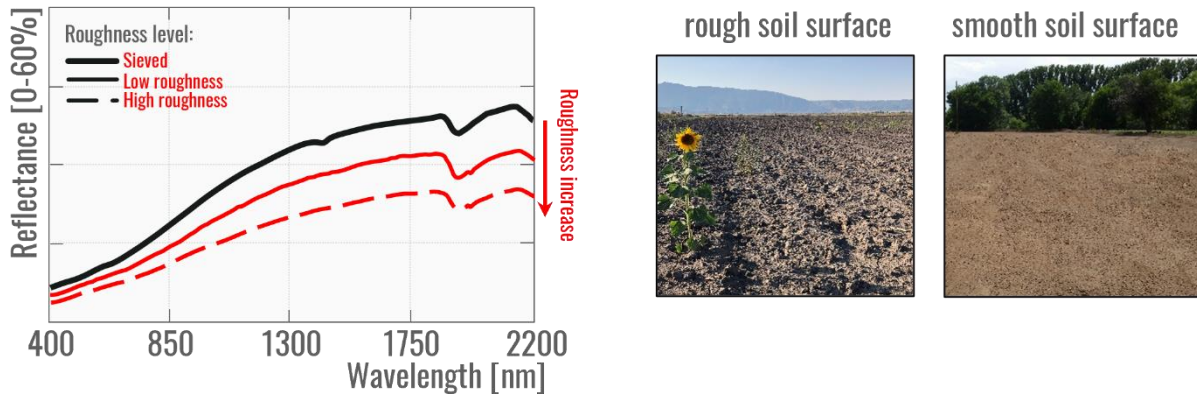


Figure 18 Impact of roughness on soil spectra and images of rough and smooth soil surfaces for illustration. from left to right: Photo in courtesy of Sabine Chabrilat; Photo in courtesy of Robert Milewski

Summary of soil physical chromophores

Most soils reflect incoming light anisotropic (uneven in the 3D-space) with a slight expression in the direction of illumination (backscattering behavior) (Ben-Dor 1999). Depending on the sun’s position, viewing angle, surface roughness and soil texture, **soil spectra are affected strongly by physical chromophores.**

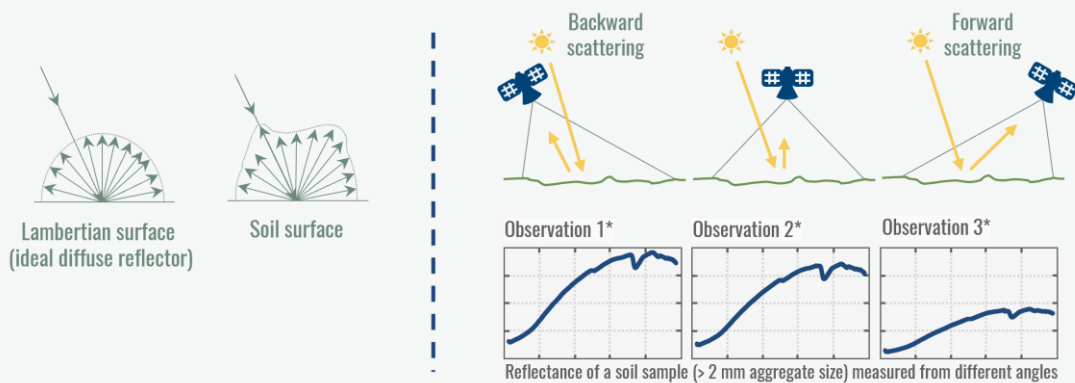


Figure 17 Summary of several effects classified as physical chromophores. Adapted from Jensen (2007) and Lillesand et al. (2008)

Summary of soil chromophores

A soil chromophore is a parameter or substance that in some way affects or alters the reflectance spectrum of soil.

Chemical chromophores are substances that absorb incident radiation at discrete energy levels, leading to diagnostic absorption features for certain materials. Chemical chromophores are: soil minerals, soil organic matter, soil salinity, soil crusts, and (to some extent) soil moisture.

Physical chromophores influence how incident radiation is scattered at the soil surface and thus **influence the shape of the spectral curve by changes in baseline reflectivity and absorption characteristic intensities.** Physical chromophores are soil particle size, surface roughness, viewing geometry, radiation intensity, and (to some extent) soil moisture.

Soil minerals

Soil organic matter

Soil salinity

Soil crusts

Soil moisture and grain size distribution

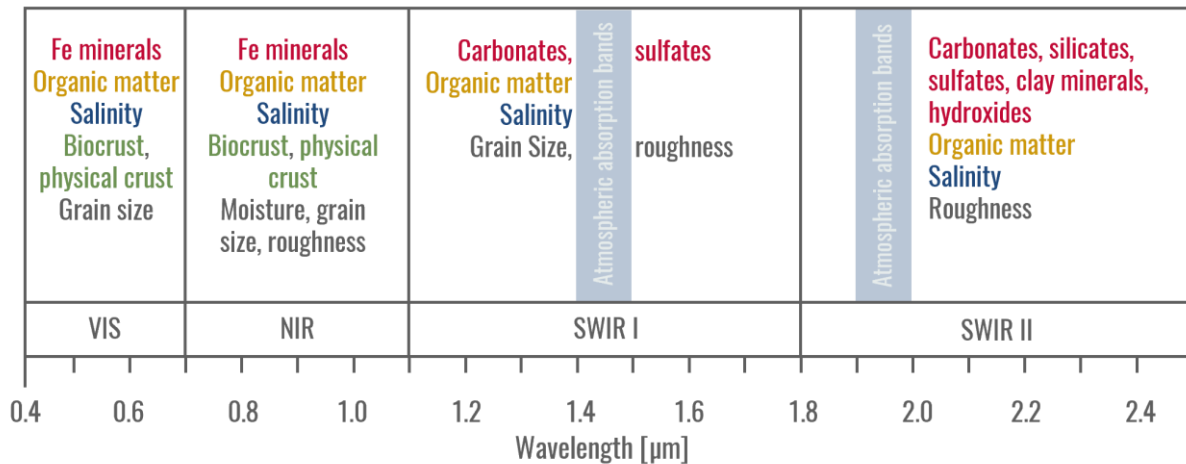


Figure 19 Summary of chemical and physical chromophores and the spectral ranges that they (most) affect. In courtesy of Herman “Charly” Kaufmann

Quiz: Geophysical and geochemical variables

Fill in the blanks

Chemical chromophores are substances that **Choose an element**, leading to diagnostic absorption features for certain materials. Everything **Choose an element** is considered a **physical chromophore**.

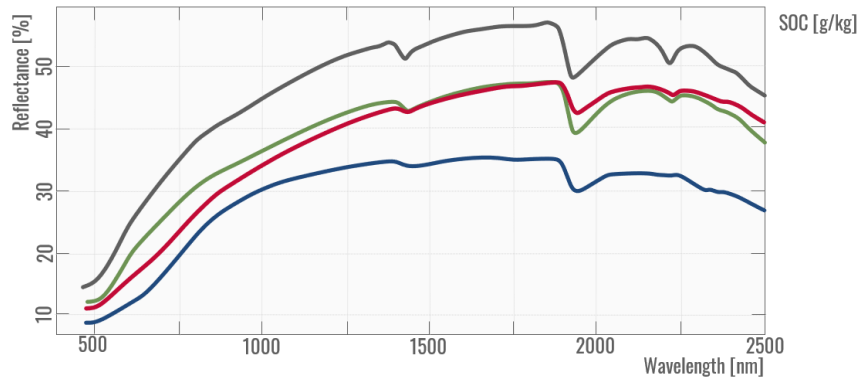
Please select only the chemical chromophores: (multiple-choice)

- Soil minerals
- Soil particle size
- Viewing geometry
- Soil organic matter
- Soil salinity
- Surface roughness
- Soil crusts
- (to some extent) Soil water
- Radiation intensity

Did you get the difference between clay and clay? (multiple-choice)

- Clay minerals act as chemical chromophores as the hydroxide ion (OH^-), occurring as lattice water in the mineral structure and as adsorbed water on the mineral surface absorbs energy in the spectral regions 1300 -1400, 1800 – 1900 and/or 2200 – 2500 nm.
- Clay particles act as physical chromophores as soil grain or aggregate size determines soil texture and surface roughness and thus has a major impact on the soil spectra. In general, albedo decreases with increasing particle size and vice versa.

Rank the different soils in the order of their SOC (soil organic carbon) content (start with the lowest).



Choose an element

Choose an element

Choose an element

Choose an element

3.3 From chromophores to soil properties (variables)

The soil chromophores outlined in the previous topic **control the spectral reflectance characteristics of soils** and are closely related to the properties or variables that we can retrieve from imaging spectroscopy data. Thereby, we distinguish between **primary variables and secondary variables**. Primary variables are directly involved in radiative transfer mechanisms. Other variables of interest, such as soil organic matter content (SOM), cation exchange capacity (CEC) or soil texture, however, result from a series of intertwined biophysical processes. These variables are so-called secondary variables. They do not respond directly to a specific diagnostic feature. Nevertheless, they can be assessed from hyperspectral remote sensing data in combination with more sophisticated approaches due to their relationships with the primary soil properties.

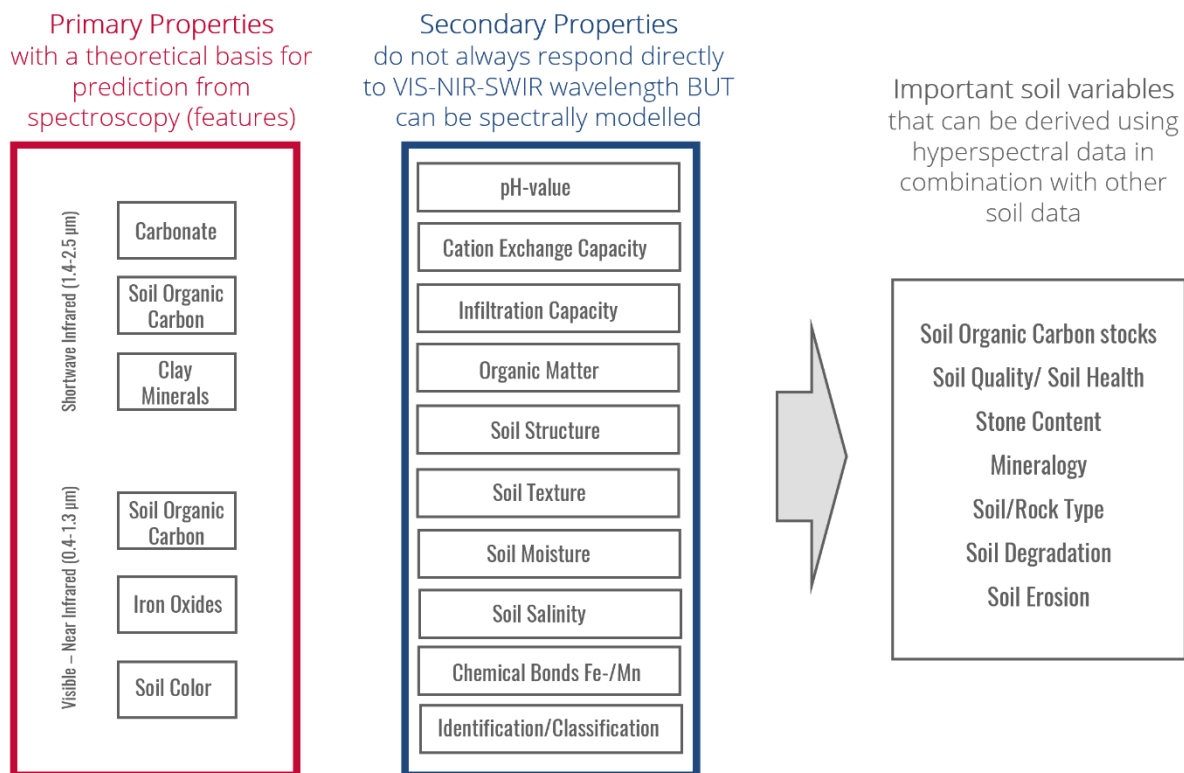
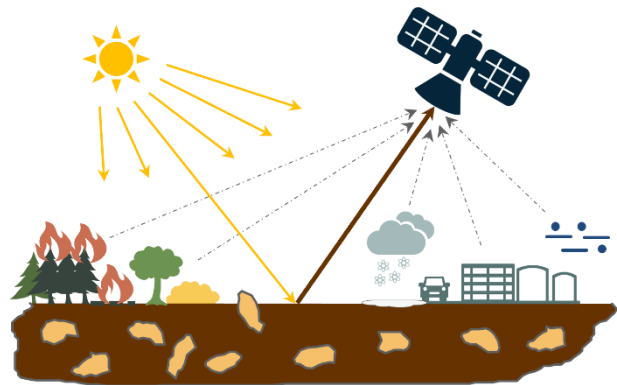


Figure 20 Primary and secondary soil properties.
In courtesy of Robert Milewski

Influencing factors – potential interferences

Due to **volume scattering**, the spectral behavior of soils is **not a simple (linear) mixture of chromophores**. Besides, **coating materials and crusts** can mask the true spectral characteristics of soils, as can high quantities of **soil organic matter** (> 3 %). Even spectrally inactive soil properties can influence the soil spectrum when interacting with soil chromophores!

In the past, many findings have been derived by regression modelling and based on optimal laboratory measurements, circumventing potentially disturbing factors such as soil moisture, soil roughness, illumination conditions or plant coverage (Cécillon et al. 2009). They can vary considerably, even under optimal laboratory conditions, making the **retrieval of soil properties with airborne or spaceborne imaging spectroscopy sensors a challenge.**



Only a small fraction of natural soils can be considered unaltered and bare. Even then, good pre-processing is required to correct an IS dataset for atmospheric influences and sensor-specific properties to optimize soil estimates.

Figure 21 Interfering factors.
In courtesy of Hermann Kaufmann

Prominent examples of influencing factors are

Biospheric interferences:

- Green and dry vegetation
- Crusts

Surface coverage interferences:

- Anthropogenic structures (e.g. infrastructure)
- Snow and ice
- Changes in the biogeochemical composition of soil surfaces, e.g. due to fires
- Natural soil sealing and crusting

Atmospheric interferences:

- Interaction of aerosol particles and atmospheric gas molecules with electromagnetic energy
- Soil BRDF (bidirectional reflectance distribution function)

Quiz: From chromophores to soil properties (variables)

With respect to soil properties, what are “primary variables”? (multiple-choice)

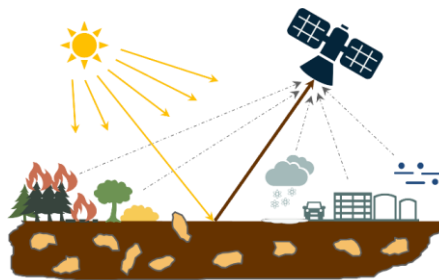
- Variables that are most important for soil applications
- Variables that are directly involved in radiative transfer mechanisms
- Variables that are not directly related to the radiative transfer mechanisms
- Variables that can be inferred directly from imaging spectroscopy data

Which of the properties below are described as primary variables? (multiple-choice)

- Carbonate
- Organic carbon
- Clay minerals
- Clay particles
- Iron oxides
- Soil color

In the image below, select the interferences that can disturb your soil property retrieval. (multiple-choice)

- Green vegetation
- Dry vegetation
- Anthropogenic surface cover
- Snow and Ice
- Changes in the biogeochemical composition of soil surfaces, e.g. due to fires
- Natural soil sealing and crusting
- Interaction of aerosol particles and atmospheric gas molecules



Only a small fraction of natural soils can be considered unaltered and bare. Even then, good pre-processing is required to correct an IS dataset for atmospheric influences and sensor-specific properties to optimize soil estimates.

3.4 Ground reference data acquisition

Campaign/Sampling design

Field measurements often complement remote sensing data as calibration and/or validation data. But before rushing to the test sites and taking measurements, it is wise to structure individual measurements into an organized campaign, putting special emphasis on the spatial patterns of variables and the optimal sampling scheme. When planning a field campaign, you should always keep in mind that the layout will significantly influence the results and that collecting variables over an entire region of interest at high resolution is often impossible. Hence, specific sampling schemes are required for optimal representation.

Please be aware that these field measurements do not represent “the truth” which is why we prefer calling them ground reference, ground measurement or ground data. Of course, errors in ground data can never be eliminated completely. You can, however, improve data quality by handling the respective instruments correctly and by considering the spatial patterns you want to capture. Some guidelines on planning field campaigns, like who should measure, where, what, how and when can be found in our reference section. Some instruments and procedures that we regularly use to gather field reference data for soil applications will be presented in the following video. Feel free to adapt the provided field protocol to your own needs.

Ground reference data acquisition in the field

How are ground reference data collected in the field? Come and join us for the Leibniz-Institute for Agrartechnology and Bioeconomy's (ATB) research site in Marquardt, just north of Potsdam!

VIDEO: Soil-04: Imaging Spectroscopy for Soil Applications – Fields and Labs



URL of the video: <https://youtu.be/cIDJE0mOw5s>

You might have noticed that we did measure quite a limited number of variables, especially if you are familiar with the work on agricultural applications of our colleagues at LMU Munich. Some more properties could be assessed in the field, for

example, soil color, but most variables really cannot be reliably assessed in the field and require lab work. We usually send our dried and sieved samples to specialized soil labs for the analyses of

- Soil texture (percentages of sand, silt and clay particles)
- Soil geochemistry (e.g. carbonates, total iron and iron oxides, organic matter, organic carbon and total carbon, nitrogen content, electrical conductivity, CEC, pH)

You will meet some of the above-mentioned variables later in the “hands-on” exercises. One thing we do often measure in the lab though are the spectra of our dried and sieved soil samples! Actually, the [FAO nowadays considers spectroscopy as “dry chemistry”](#) compared to lab chemical analyses that are considered “wet chemistry”. In order to show you how we do take soil spectral measurement – with our field spectroradiometer – we’ve taken you to our spectral lab at the GFZ in the basic MOOC. If you haven’t seen the video yet, you can do so here:

VIDEO: Basic-13: Sensor technologies & data acquisition techniques: ASD Lab



URL of the video: <https://youtu.be/Ewhk-rZjOTI>

Quiz: Ground reference data acquisition

Which of the variables below can only be assessed or measured in the lab?

(multiple-choice)

- Soil texture (percentages of sand, silt and clay particles)
- Soil spectra
- Soil geochemistry
- Soil moisture
- Soil surface roughness

What do you need to consider when collecting soil spectra in the field? (multiple-choice)

- To allow sufficient instrument warm-up time
- To wear dark clothes
- To look out for overpassing satellites
- To avoid bright or reflecting surfaces near the target
- To not cast a shadow on anything you want to measure
- To stick to bare soil areas, preferably in the middle of the field
- To wear a hat
- To measure under stable illumination conditions
- To repeat white reference and, if necessary, optimization
- To always keep notes on everything

3.5 Resources section: 'Imaging spectroscopy for soil applications'

In this section, we have assembled resources used for the creation of this lesson that we recommend for further reading as they provide a lot more detail. Please remember that this selection is not a complete overview of all resources – if you think an important resource is missing, let us and your fellow students know (e.g. in the discussion forum).



Sources and further reading

Topic 3.1: Imaging spectroscopy of soil

- Ben-Dor, E., Irons, J. R., & Epema, G. F. (1999). **Soil reflectance**. *Remote sensing for the earth sciences: Manual of remote sensing*, 3, 111-188.
- Clark, R. N. (1999). **Spectroscopy of rocks and minerals, and principles of spectroscopy remote sensing for the earth sciences**. *Manual of Remote Sensing*, 3rd Edition: John Wiley and Sons, New York, NY, 3–58.
- Demattê J.A.M., Morgan, C.L.S., Chabrilat S., Rizzo, R., Franceschini, M.H.D., Terra, F.daS., Vasques. G.M., and Wetterlind, J. (2015): **Spectral Sensing From Ground to Space in Soil Science: State of the Art, Applications, Potential and Perspectives**, In: P.S. Thenkabail (Ed), *Remote Sensing Handbook – Three Volume Set: Land Resources Monitoring, Modeling, and Mapping with Remote Sensing*, CRC Press, 661-732, 833pp. ISBN-10: 1482217953.
- Hunt, G. R. (1977). **Spectral signatures of particulate minerals in the visible and near infrared**. *Geophysics*, 42(3), 501-513.
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- Ustin S., Roberts D., Gamon J., Asner G., Green R. (2004): **Using imaging spectroscopy to study ecosystem processes and properties**, *Bioscience*, 54 (6), 523–534.

Topic 3.2: Soil chromophores

- Ben-Dor, E., Irons, J. R., & Epema, G. F. (1999). **Soil reflectance**. *Remote sensing for the earth sciences: Manual of remote sensing*, 3, 111-188.
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- Blume, H.-P., Brümmer, G. W., Schwertmann, U., Horn, R., Kögel-Knabner, I., Stahr, K., Auerswald, K., Beyer, L., Hartmann, A., Litz, N., Scheinost, A., Stanjek, H., Welp, G., & Wilke, B.-M. (2002). **Lehrbuch der Bodenkunde / Scheffer/ Schachtschabel.**
- Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T., & van Wesemael, B. (2019). **Imaging spectroscopy for soil mapping and monitoring.** *Surveys in Geophysics*, 40(3), 361-399.
- Hunt, G. R. (1971). **Visible and near-infrared spectra of minerals and rocks: III. Oxides and hydro-oxides.** *Modern Geology*, 2, 195-205.
- Hunt, G. R. (1977). **Spectral signatures of particulate minerals in the visible and near infrared.** *Geophysics*, 42(3), 501-513.
- Hunt, G. R. (1979). **Near-infrared (1.3-2.4 μ m) spectra of alteration minerals; potential for use in remote sensing.** *Geophysics*, 44(12), 1974-1986.
- Lefèvre, C., Rejik, F., Alcantara, V., & Wiese, L. (2017). **Soil organic carbon: the hidden potential.** Food and Agriculture Organization of the United Nations (FAO).
- Milewski, R., Chabrillat, S., Brell, M., Schleicher, A. M., & Guanter, L. (2019). **Assessment of the 1.75 μ m absorption feature for gypsum estimation using laboratory, air-and spaceborne hyperspectral sensors.** *International Journal of Applied Earth Observation and Geoinformation*, 77, 69-83.
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- Pu, R. (2017). **Hyperspectral remote sensing: Fundamentals and practices.** CRC Press.
- Richter, N. (2010). **Pedogenic iron oxide determination of soil surfaces from laboratory spectroscopy and HyMap image data** (Doctoral thesis, Humboldt-Universität, Berlin, Germany).
- Stenberg, B., Viscarra Rossel, R. A., Mouazen, A., & Wetterlind, J. (2010). **Chapter five – visible and near infrared spectroscopy in soil science.** *Advances in agronomy*, 107, 163–215.
- Tarbuck, E. J., Lutgens, F. K., & Lammerer, B. (2009). **Allgemeine Geologie.** 9. Aufl. München: Pearson Studium.

Topic 3.4: Ground reference data acquisition

- Field Protocol – see 'Materials' at Landing Page

3.6 Quiz: Introduction to imaging spectroscopy for soil applications

Fill in the blanks

In general, increases in particle size cause a **Choose an element** in overall reflectance. Also, reflectance generally decreases with **Choose an element** organic matter and/or moisture content.

Since the major constituents of soil minerals (O, Si, Al, and Mg) do not exhibit absorption features in the VNIR and SWIR range, soil spectral reflectance characteristics are mainly influenced by ... (multiple-choice)

- ... iron-oxide content
- ... clay mineral composition
- ... organic matter content
- ... texture and surface roughness
- ... salinity
- ... moisture content
- ... dry vegetation residues

Dry vegetation and bare soil can be distinguished best based on ... (single-choice)

- ... the cellulose absorption feature around 2200 nm
- ... the cellulose absorption feature between 700 and 1300 nm
- ... their water content

Even small amounts of Iron oxides can alter VNIR spectra significantly, causing broad absorption features particularly around... (single-choice)

- ... 400 nm
- ...400 nm, 700 nm and 870 nm
- ...1400 nm and 1700 nm
- ...2100 nm

What is the correct definition of a chemical chromophore and a physical chromophore? (multiple-choice)

Sort elements

Chemical chromophore: **Choose an element**

Physical chromophore: **Choose an element**

Incorrect definition: **Choose an element**

Select ONLY the physical chromophores: (multiple-choice)

- Soil minerals
- Soil particle size
- Viewing geometry
- Soil organic matter
- Soil salinity
- Surface roughness
- Soil crusts
- (to some extent) Soil water
- Radiation intensity

Did you get the difference between clay and clay? (multiple-choice)

- Clay minerals act as chemical chromophores as the hydroxide ion (OH^-), occurring as lattice water in the mineral structure and as adsorbed water on the mineral surface absorbs energy in the spectral regions 1300 -1400, 1800 – 1900 and/or 2200 – 2500 nm.
- Clay particles act as physical chromophores as soil grain or aggregate size determines soil texture and surface roughness and thus has a major impact on the soil spectra. In general, albedo decreases with increasing particle size and vice versa.

Which of the properties below are described as primary variables? (multiple-choice)

- Carbonate
- Organic carbon
- Clay minerals
- Clay particles
- Iron oxides
- Soil color

Which interferences can disturb your soil property retrieval? (multiple-choice)

- Green vegetation
- Dry vegetation
- Anthropogenic surface cover
- Snow and ice
- Changes in the biogeochemical composition of soil surfaces, e.g. due to fires
- Natural soil sealing and crusting
- Interaction of aerosol particles and atmospheric gas molecule

4 Methodological aspects

Welcome to this methodological lesson! Did you ever wonder during the previous lesson how to go about actually retrieving soil properties (or variables) from hyperspectral imagery and/or how to connect remote sensing with field data? Actually, it's less complicated than you might think. However, there are quite a few methods out there, which is why we will first give a general overview of methods applied in soil imaging spectroscopy. Then, we will provide more detailed information on the state-of-the-art techniques you will be trained in throughout this course. You'll also learn about data and software resources as well as the general workflow. As usual, what may sound dull is actually a really fun lesson with lots of interactive content and videos! Charly will give you some more details on the learning objectives in the video below. Ready?

VIDEO: Soil-05: Imaging Spectroscopy for Soil Applications – Lesson 02 Intro



URL of the video: <https://youtu.be/T29Cj7ZO1sw>

Let's move on with the first topic of this lesson!

4.1 Data and software resources

Data resources were quite a big topic in the basic MOOC 'Beyond the Visible: Introduction to Hyperspectral Remote Sensing'. In this topic, we've linked some of the resources that we think might be important if you are working in a soil context, including some updates and additional materials.

Data

For a long time, the availability of hyperspectral data was limited to expensive flight campaigns for small, selected areas with infrequent revisits (if at all). The "applications" were mostly related to scientific questions and method development rather than

designed to answer real-world questions. Well, with the recent and upcoming launches of (additional) hyperspectral satellites, this is going to change!

Spaceborne

There are already a number of Earth observing imaging spectrometers in space today. Often, the data is made available free of charge (for scientific purposes). In this section, we would like to introduce you to – or remind you of – some easily accessible data sources for VNIR-SWIR **spaceborne** imaging spectroscopy data, starting with the most recent missions.

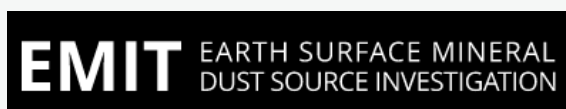
EnMAP



EnMAP by the German Space Agency (DLR), is the German hyperspectral observation satellite with more than 200 bands in the VNIR to SWIR range. EnMAP was launched into space on April 1st 2022 and data is available for more and more regions of the world.

There are two main entry points to **get EnMAP data using the Data Access Portal**: the EnMAP Instrument Planning Portal and the EOWEB® GeoPortal. Together with the EnMAP ground segment, we have produced four screencasts (available via YouTube) that explain the process: On the EnMAP Instrument Planning Portal users can [register](#), [submit proposals](#), and [plan and request future orders](#). The [EOWEB GeoPortal](#) contains the full EnMAP Data archive.

EMIT



EMIT is an imaging spectrometer designed to map the composition of areas that produce mineral dust accurately. It was developed at NASA's Jet Propulsion Laboratory and launched on July 14, 2022.

Unlike the other sensors on this list, EMIT is operated from the International Space Station (ISS), resulting in the Earth coverage being limited to about 55-degree latitude. EMIT is not based on user requests, the [data portal](#) is very convenient and easy to use.

PRISMA



PRISMA by Italian Space Agency (ASI), is an Earth observation satellite with innovative electro-optical instrumentation which combines a hyperspectral sensor with more than 200 bands in the VNIR to SWIR range with a panchromatic camera. The satellite was successfully launched in March 2019. Users can obtain archive data and request new data acquisitions after registering in the [PRISMA data portal](#).

With the kind cooperation of ASI, we have produced three screencasts available via YouTube. Here, you can get a short overview of the PRISMA mission and learn step by step how to [register in the PRISMA data portal](#), [how to access the PRISMA data catalogue to search for archived data](#), and [request new PRISMA acquisition in the PRISMA data portal](#).

Hyperion

The first VNIR-SWIR imaging spectrometer that launched into space in 2000 was the **Hyperion imaging spectrometer**, a technology demonstrator aboard NASA's Earth observing mission EO-1. Despite being planned as a one-year mission, the sensor was in operation until 2017 and **data is available via the [USGS Earth Explorer Portal](#)**. This portal provides access to a range of other remote sensing data and products in addition to Hyperion datasets. The USGS provides some helpful guidance videos (though not specifically on downloading Hyperion data): An [EarthExplorer Introduction](#) discussing the basics of using EarthExplorer or an [EarthExplorer Search Criteria](#) introducing the available search options.

Airborne

Right, airborne data are expensive to acquire and acquisitions are rare. Nevertheless, some projects are generous and you can **download data for free!** Find out how in the section below – or use it as a small reminder.

AVIRIS-NG Campaign Portal



AVIRIS-Next Generation is an imaging spectrometer that measures reflected radiance at 5 nm intervals in the VNIR-SWIR spectral range from 380-2500 nm. The sensor has already been flown in several airborne campaigns in many countries. The [AVIRIS-NG Data Portal](#) provides an **overview of the campaign data and the possibility to download L1 and L2 data products**. In addition, reflectance data of the ESA CHIME & SBG AVIRIS-NG Europe 2021 campaign have been made available for download at the [campaign website of ARES](#), the Airborne Research Facility for the Earth System at the University of Zurich.

Note: If L1 and L2 means nothing to you, please check out our [Basic MOOC: Beyond the visible – Introduction to Hyperspectral Remote Sensing](#) and our mini-MOOC [Beyond the Visible – EnMAP data access and image preprocessing techniques](#).

EnMAP Campaign Portal



The [EnMAP Campaign Portal](#) provides access to airborne hyperspectral image data sets along with simulated EnMAP data that was generated using the EnMAP end-to-end simulation tool (EeteS). In addition, **associated in-situ data from field and laboratory measurements** are provided. The flight campaigns were carried out in the framework of the EnMAP preparatory science program to support method and application development in the prelaunch phase of the EnMAP satellite mission. A metadata portal has been

Soil Spectral Libraries (SSL's)

In soil spectroscopy, **spectral libraries play an important role, e.g. for the calibration and validation of models but also to test entirely new algorithms.** Therefore, quite a number of specific soil spectral libraries exist. We have listed several prominent and very big ones below. There are many more regional or national ones but they are not the focus here. Anyway, if you think we missed an important resource, please share it with the community via the discussion forum.

Global Spectral Database

The global soil visible–near infrared (vis–NIR) spectral library is one of the largest and most diverse database of its kind, containing spectra recorded in different laboratories using different spectrometers and methods. New contributions to the library are explicitly encouraged for the SSL to evolve into a dynamic and easily updatable database with even better global coverage. It is described by Viscarra Rossel et al. (2016).

World Soil Information (ISRIC) spectral library

“The [ICRAF-ISRIC Soil VNIR Spectral Library](#) contains visible near infrared spectra of 785 soil profiles (4,438 samples) selected from the Soil Information System of the International Soil Reference and Information Centre (ISRIC). The samples consist of all physically archived samples at ISRIC in 2004 for which soil attribute data was available. The spectra were measured at the World Agroforestry Center (ICRAF) Soil and Plant Spectral Diagnostic Laboratory. The samples originate from 58 countries spanning Africa, Asia, Europe, North America, and South America. Associated attribute data, such as geographical coordinates, horizon (depth), and physical and chemical properties, are provided as separate tables” ([ICRAF, 2021](#)). See also Shepherd et al. 2003.

European LUCAS database

The European Commission extended its periodic Land Use/Land Cover Area Frame Survey known as “[LUCAS](#)” in 2009. Therefore, the main properties of topsoil were sampled and analysed in 25 EU Member States, representing the first attempt to build a consistent spatial database of soil across the EU based on standard sampling and analytical procedures.

In this survey, topsoil (0-20 cm) was collected following a standardized sampling procedure and physical and chemical analyses of all samples were performed in a single laboratory (percentage of coarse fragments, particle size distribution, pH, cation exchange capacity, organic carbon, carbonate, phosphorous, total nitrogen, and extractable potassium content, as well as hyperspectral properties. The final 2009 database contains about 20,000 geo-referenced samples. The data are freely available and can be downloaded after prior registration. In 2015 and 2018, the LUCAS database was updated to contain even more samples from all 28 EU member states as well as additional soil properties.

Detailed insight to the design and methodology of the data collection and laboratory analysis are provided in the report [LUCAS Topsoil Survey: methodology, data and results](#).

GEO-CRADLE Spectral Library (GSSL)

The GEO-CRADLE spectral library (GSSL) is a result of the GEO-CRADLE project, a collaboration of nine national research organizations spanning three continents. Their goal was to construct a regional data framework of soil VIS-NIR-SWIR spectra in the range of 350 to 2500nm covering an area of well-recognized gaps in soil data. The GSSL is composed of 1,760 samples from 1,017 soil profiles in nine countries across the Balkan, Middle East, and North Africa region. The selection of samples involved accessing national soil data archives and collecting samples through field surveyors. To ensure the consistency of the data collection and analysis, the data acquisition followed general guidelines, standards, and protocols. Around 58% of the spectra in the GSSL are from the top soil layer (0-30cm), 20% were collected at a depth of 30-60cm and another 20% were collected within 60-100cm. Only 2% of the data originates from samples gathered at depths > 100cm. The data are freely available and can be downloaded from the [GEO-CRADLE datahub](#) (i-BEC et al. 2019, Tziolas et al. 2019).

Open Soil Spectral Library

The Open Soil Spectral Library (OSSL) is a large database of soil spectral data that allows users to combine and analyze soil information. It comprises multiple interrelated components. One main component is a harmonized database containing spectral libraries in the VNIR and MIR regions of the electromagnetic spectrum including commonly measured soil properties.

The data can be directly accessed and visualized through the OSSL Explorer, the OSSL API, or via [downloading](#) parts of the database. Another important component of the OSSL is the [OSSL Engine](#). Here users can upload their own spectra and the associated soil properties will be estimated through a set of machine learning models. It is important to note that as the data set was mostly trained with data from the USA and Europe the calibration models primarily mirror soil characteristics from the USA and Europe (Safanelli et al. 2019, Sandermann 2021).

The Brazilian Soil Spectral Library

The Brazilian Soil Spectral Library (BSSL) is the first Brazilian soil spectral library and comprises 39,284 soil samples from 65 contributors of all 26 states (status 2019). It standardizes and allows the examination of soil spectra in the 350 to 2500 nm range of Brazilian soils, including important soil characteristics such as clay, sand, soil organic carbon, cation exchange capacity, pH, and base saturation. Brazilian soil types can be categorized into six basic patterns of spectral signatures where environmental conditions explain the differences in spectra. The BSSL is accessible through an [online platform](#) showing the Brazilian Map with all the BSSL data and simplifies the communication between users and researchers. The BSSL database is continually augmented with new information, thereby enhancing its representativeness in Brazil (Demattê et al. 2019).

The Chinese Spectral Library

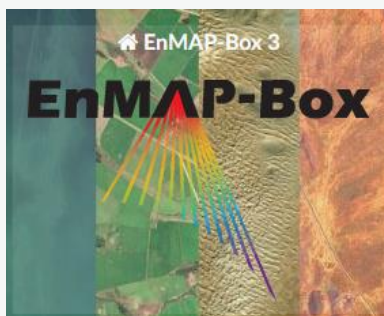
The Chinese Soil Spectral Library (CSSL) consists of 1,581 soil samples which were collected in 14 provinces in China (status 2014). The samples were taken from the topsoil at a depth of 0 to 20 cm and represented 16 soil groups of the Genetic Soil Classification of China. The samples were air-dried and sieved before measuring the diffusive reflectance spectra in the range between 350 and 2500 nm with a portable vis-NIR spectrometer. The measurements took place under laboratory conditions. The CSSL especially focuses on providing soil organic matter concentration predictions using a large-scale spectral library (Shi et al. 2014).

Software

With the increasing availability of hyperspectral data, options to visualize and process the data are increasing, too. [Commercial options such as ENVI](#) have been around

for about two decades and are certainly comfortable to use. In addition, the capabilities of **Geographic Information Systems (GIS)** such as the **free and open source QGIS** software, are growing and you can easily display your data and perform simple analyses such as the calculation of spectral indices. QGIS **plug-ins such as the EnMAP-Box** allow for more complex hyperspectral analyses. If you like working with code, some helping hands provide assistance in getting started with hyperspectral analyses, e.g., using **R or Python**. However, as not everyone is familiar with the use of code, **in this course we'll be working with the EnMAP-Box.**

EnMAP Box



There are several software options that facilitate the visualization and analyses of hyperspectral data. One of these options is the **EnMAP-Box**, a **free and open source Python plug-in for QGIS**, specifically **designed to process and visualize imaging spectroscopy data** from the EnMAP mission, but also any other optical remote sensing data. The EnMAP-Box was developed as part of the EnMAP preparatory science program to facilitate advanced processing of high dimensional spectral remote sensing data and enhanced visualization as well as the exploration of multi-band remote sensing data and spectral libraries in a GIS environment. The plug-in consists of a graphical user interface for data visualization and spectral library management, a set of advanced general and application-oriented algorithms, and a high-level application programming interface (EnMAP API). The EnMAP-Box can be started from QGIS or stand-alone and is registered in the QGIS plug-in repository. We will guide you through the installation, first steps and agricultural applications **using the EnMAP-Box in the next lesson.**

Earthbit PRISMA Toolbox



Planetek Italia, responsible for the design and development of the PRISMA geocoding sub-system, released [the earthbit PRISMA Toolbox v1.0](#) (for MS Windows systems) in September 2023. The toolbox allows to import, view and convert L1, L2B, L2C, L2D PRISMA products in a simple way and enables users to interact in a quick manner with the spectral bands and the metadata of the products.

Quiz: Data and software resources

Did you check out the portals? Which one offers airborne data AND corresponding ground reference data for direct download? Note: For the others, ground reference data are often available upon request from the contact persons named for the respective campaign. (single-choice)

- EnMAP campaign portal
- AVIRIS portal
- ARES portal

Spaceborne imaging spectroscopy data is currently freely available from the sensor: (multiple-choice)

- PRISMA
- EnMAP
- Hyperion
- SBG

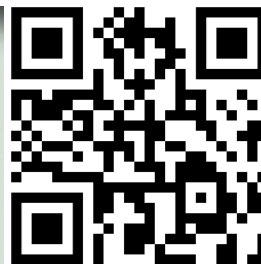
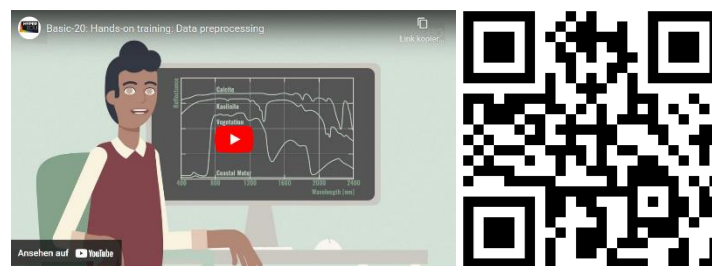
If you want to visualize hyperspectral data, you can do this for FREE by using... (multiple-choice)

- Code, e.g. R or Python
- Some GIS software, e.g. the free and open source QGIS
- Free QGIS plugins such as the EnMAP-Box
- Specific imaging spectroscopy software such as ENVI

4.2 Methods

There are a **variety of methods for analyzing** the high information content of imaging spectroscopy data, depending on the application and target variables. First of all, it is important that your data are properly preprocessed. And even if the data comes processed, it might be helpful to understand the different preprocessing steps. How do you get from physically non-interpretable digital numbers originally acquired by the sensor to physical units that are transferable and comparable? Well, Charly explained the general process (including some considerations on data selection) in the basic MOOC. If you are already familiar with the topic of preprocessing, just skip the next video. If, on the other hand, you would like to learn even MORE about preprocessing, we recommend our course on EnMAP data access and preprocessing.

VIDEO: Basic-20: Hands-on training: Data preprocessing



URL of the video: <https://youtu.be/drqFyMmyPI0>

In the basic MOOC, we differentiated between **Classification and Quantification**. Now, we look at these methods from a soil spectroscopy perspective: In the following **video**, Charly will give you a general **overview of methods that are widely used in soil imaging spectroscopy**.

VIDEO: Soil-06: Imaging spectroscopy for Soil Applications – Overview Methods

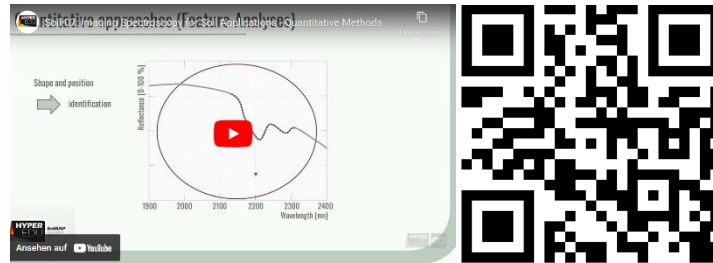


URL of the video: <https://youtu.be/D3H9TTIQca0>

In this course, we want to **focus on feature analyses and machine learning** as they are most frequently used and thus very established and robust. In the following **video**,

Charly will be a bit **more specific on** how feature analyses actually work and which machine learning models are frequently used:

VIDEO: Soil-07: Imaging spectroscopy for Soil Applications – Quantitative Methods



URL of the video: <https://youtu.be/UtaqBlyGkaY>

Quiz: Methods

Many of the analyses described in this topic require reference data for their full potential – what can serve as reference? (multiple-choice)

- Spectra (in this context often called “endmembers”)
- Historic maps
- In-situ measurements, e.g. of one or several soil geochemical properties

State-of-the-art methods for the quantitative retrieval of soil properties are ... (multiple-choice)

- Spectral Feature Analyses, such as provided by the EnSoMAP toolset in the EnMAP-Box
- Radiative transfer modelling approaches
- Statistical multivariate machine learning approaches
- Spectral Mixing Analyses also known as Linear Spectral Unmixing, used among other methods to detect Fractional coverage of green vs dry vegetation vs soils

What are the advantages of spectral feature analyses? (multiple-choice)

- They allow for the semi-quantification of soil geochemical and -physical properties without the need for any calibration data
- With in-situ information, even absolute quantification is possible
- The spectral feature analysis is the most accurate technique and highly transferable between different ecoregions
- The spectral feature analysis is often quite robust and easy to apply

Fill in the blanks

Choose an element used in soil spectroscopy are statistical multivariate machine learning approaches, also referred to as **Choose an element**. These methods **Choose an element** require in-situ information and allow for the retrieval of soil type, soil minerals and soil bio- and geophysical properties. To reduce the risk of overfitting the machine learning model, the database should ideally **Choose an element**.

Identify methods used to prepare spectral data for the application of soil specific algorithms: (multiple-choice)

- Careful inspection of spectra for “spikes” that the algorithms may misinterpret as “features”
- Smoothing, e.g. Savitzky-Golay
- Removal of bands, for example in the spectral atmospheric water absorption ranges
- Normalizations, for example “continuum removal”
- Data transformations, for example derivatives or absorbance
- In-situ measurements, e.g. of one or several soil geochemical properties
- Dimensionality reduction, for example Minimum Noise Fraction Transformation or Principal Component Analysis
- Cosmetic correction
- Masking of any pixels that are not bare (or at least semi bare) soil

We have mentioned “continuum removal” several times – but actually, what is it? (single-choice)

- A continuum describes something that follows on from one another without interruption – like a spectrum. Thus, “continuum removal” describes the removal of spectral samples not suited for the analyses at hand.
- The “continuum” is simply a convex hull that can be calculated for (a) the entire spectrum or (b) a specific absorption area (or feature). Removal of the continuum results in a normalization of the spectra and allows for comparison of absorption depths from a common baseline (that equals 1).
- It is a science fiction TV-series from the year 2012

4.3 Workflow

Now, imagine you want to answer your own research questions using imaging spectroscopy data – **what would the general workflow be?**

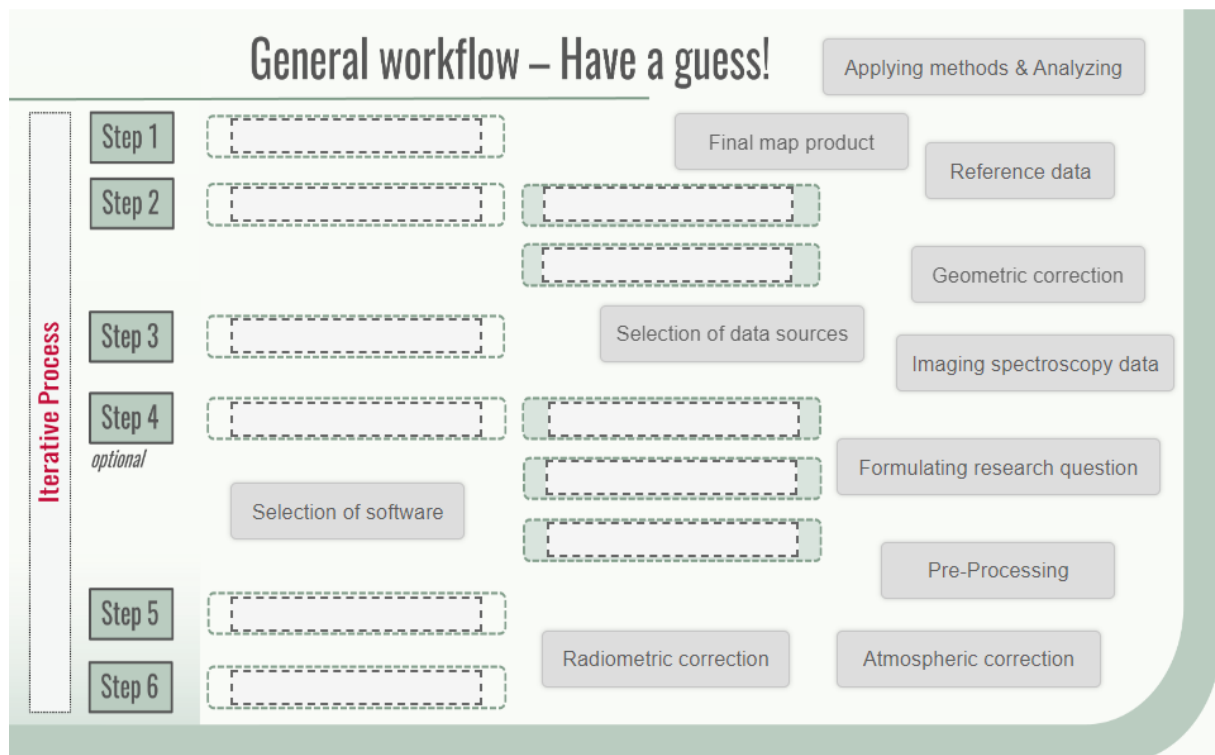
If you have participated in the basic MOOC ‘Beyond the Visible – Introduction to Hyperspectral Remote Sensing’ or our course on Agricultural Applications, the following exercise will seem familiar. You are right, it is and you might have solved it before ... you see, we think it is important to become familiar with soil applications in the context of an entire workflow, including the final map product, preprocessing, choice of software, data acquisition etc.

Oh, final map before preprocessing is the wrong order? Well, have a guess then and **place the six different steps involved including some more concrete sub-steps (Step 2 and Step 4) correctly!**



Interactive graph on the General Workflow

Available under this [link](#).



Of course, the workflow shown is very abstract and simplified and you might experience situations where you must iteratively go back and adjust. Nevertheless,

the exercise shows that the path to a final, qualitative (or even quantitative) map product based on imaging spectroscopy data involves many steps whose precise definition requires intensive thought and consideration. You can find the solution below.

While the formulation of the research question is up to you, we will get into more detail on the methods in the next lesson, including some very useful tips and initial practical experience.



Do you want to **share your pending research question with the MOOC community?** Please **use the discussion forum** of this topic to do so! We are very keen to hear from you!

Quiz: Workflow

Which preprocessing steps should be applied to hyperspectral data? (multiple-choice)

- Atmospheric correction
- Radiometric correction
- Cosmetic correction
- Geometric correction

Why can it be useful to apply dimensionality reduction before or as part of actual image analysis? (multiple-choice)

- Because it can speed-up processing and reduce computational costs
- Because hyperspectral data are often highly redundant and carry highly inter-correlated information
- Because redundant data introduce noise and may lead to suboptimal model performances
- Because the hundreds of contiguous bands are so confusing

Besides dimensionality reduction, which methods are frequently used to prepare spectral data for the application of soil specific algorithms? (multiple-choice)

- Careful inspection of spectra for “spikes” that the algorithms may misinterpret as “features”
- Smoothing, e.g. Savitzky-Golay
- Interpolation of missing band information
- Removal of bands, for example in the spectral atmospheric water absorption ranges
- Normalizations, for example “continuum removal”
- Data transformations, for example derivatives or absorbance
- Cosmetic correction
- Masking of any pixels that are not bare (or at least semi bare) soil

The overall workflow for the retrieval of soil properties using imaging spectroscopy data consist of ... (multiple-choice)

- Selecting orthorectified reflectance data
- Ensuring data quality, for example, by spectral smoothing or removing noisy bands
- Selecting bare or at least semi-bare soil pixels to which the subsequent algorithms can be applied – masking using spectral features or spectral unmixing can assist
- Considering spectral normalization, for example, continuum removal, or another transformation, like principal components, higher derivatives or absorbance
- Applying your selected soil algorithm
- Projecting the (semi)quantitative soil values onto geographical maps

4.4 Resources section: 'Methodological aspects'

In this section, we have assembled resources used for the creation of this lesson that we recommend for further reading as they provide a lot more detail on the different topics. Please remember that this selection is not a complete overview of all resources – if you think an important resource is missing, let us and your fellow students know (e.g. in the discussion forum).



Sources and further reading

Topic 4.1: Data and software

- Spectral Index database <https://www.indexdatabase.de/db/i.php>

EnMAP Data

- www.enmap.org
- <https://eoweb.dlr.de>
- Guanter, L., Kaufmann, H., Segl, K., Foerster, S., Rogass, C., Chabrillat, S., Kuester, T., Hollstein, A., Rossner, G., Chlebek, C., Straif, C., Fischer, S., Schrader, S., Storch, T., Heiden, U., Mueller, A., Bachmann, M., Mühle, H., Müller, R., Habermeyer, M., Ohndorf, A., Hill, J., Buddenbaum, H., Hostert, P., Van der Linden, S., Leitão, P.J., Rabe, A., Doerffer, R., Krasemann, H., Xi, H., Mauser, W., Hank, T., Locherer, M., Rast, M., Staenz, K., Sang, B. (2015). **The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation**. Remote Sens., 7, 8830-8857. <https://doi.org/10.3390/rs70708830>
- Jakimow, B., Janz, A., Thiel, F., Okujeni, A., Hostert, F., and van der Linden, S. (2023). **"EnMAP-Box: Imaging spectroscopy in QGIS"**. SoftwareX, vol. 23, p. 101507, doi: <https://doi.org/10.1016/j.softx.2023.101507>

PRISMA Data

- <https://prisma.asi.it>
- R. Loizzo et al. (2018): **"Prisma: The Italian Hyperspectral Mission"** IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium, pp. 175-178, doi: 10.1109/IGARSS.2018.8518512.

USGS Earth Explorer Portal (Hyperion)

- <https://earthexplorer.usgs.gov/>
- An EarthExplorer Introduction discussing the basics of using EarthExplorer (by USGS): <https://www.youtube.com/watch?v=eAmTxsg6ZYE>

- An EarthExplorer Search Criteria discussing the available search options (by USGS): <https://www.youtube.com/watch?v=CVsgjp9jRyA>
- A tutorial on Hyperion (by NASA ARSET, 29:53 -37:30): <https://www.youtube.com/watch?v=x7l6n7njVPo>
- A recent webinar series on imaging spectroscopy (by NASA ARSET): <https://appliedsciences.nasa.gov/join-mission/training/english/arset-hyperspectral-data-land-and-coastal-systems>

AVIRIS-NG

- Overview of campaign data and download possibility for L1 and L2 data products: <https://avirisng.jpl.nasa.gov/dataportal/>
- Data of the ESA CHIME & SBG AVIRIS-Next Generation Europe 2021 campaign available for download from https://ares-observatory.ch/esa_chime_mission_2021/

EnMAP flight campaign data

- EnMAP data simulated from airborne data (https://www.enmap.org/data_tools/simulated/)
- Overview of campaign data direct links to the dataset landing pages: https://www.enmap.org/data_tools/flights or, alternatively, search and data download via https://dataservices.gfz-potsdam.de/portal/?q=hyperspectral*

Soil Spectral Libraries

- Demattê, J. A., Dotto, A. C., Paiva, A. F., Sato, M. V., Dalmolin, R. S., Maria do Socorro, B., ... & do Couto, H. T. Z. (2019). **The Brazilian soil spectral library (BSSL): A general view, application and challenges.** *Geoderma*, 354, 113793.
- I-BEC, TAU, USCM, UZAY, FASF, IPB, SRTI, CUT, CEDARE (2019). **The regional soil spectral library.** <http://datahub.geocradle.eu/dataset/regional-soil-spectral-library>.
- ICRAF (2021). **ICRAF Soil and Land Health Theme (World Agroforestry Centre). ICRAF-ISRIC Soil VNIR Spectral Library.** <https://data.worldagroforestry.org/dataset.xhtml?persistentId=doi:10.34725/DVN/MFHA9C> (accessed 16.02.2024).
- LUCAS (2009). **LUCAS: Land Use and Coverage Area frame Survey.** <https://esdac.jrc.ec.europa.eu/projects/lucas> (accessed 16.02.2024).
- Safanelli, J. L., Hengl, T., Sanderman, J., & Parente, L. (2021). **Open Soil Spectral Library (training data and calibration models) (v1.2) [Data set].** Zenodo. <https://doi.org/10.5281/zenodo.7599269>

- Sandermann (2021). **Introducing the Open Soil Spectral Library.** <https://soilspectroscopy.org/introducing-the-open-soil-spectral-library/> (accessed 16.02.2024).
- Shepherd, K. D., Palm, C. A., Gachengo, C. N., & Vanlauwe, B. (2003). **Rapid characterization of organic resource quality for soil and livestock management in tropical agroecosystems using near-infrared spectroscopy.** *Agronomy Journal*, 95(5), 1314-1322.
- Shi, Z., Wang, Q., Peng, J., Ji, W., Liu, H., Li, X., & Viscarra Rossel, R. A. (2014). **Development of a national VNIR soil-spectral library for soil classification and prediction of organic matter concentrations.** *Science China Earth Sciences*, 57, 1671-1680.
- Toth, G., Jones, A., Montanarella, L., Alewell, C., Ballabio, C., Carre, F., ... & Yigini, Y. (2013). **LUCAS Topsoil Survey-methodology, data and results.** https://esdac.jrc.ec.europa.eu/ESDB_Archive/eusoils_docs/other/EUR26102E_N.pdf
- Tziolas, N., Tsakiridis, N., Ben-Dor, E., Theocharis, J., & Zalidis, G. (2019). **A memory-based learning approach utilizing combined spectral sources and geographical proximity for improved VIS-NIR-SWIR soil properties estimation.** *Geoderma*, 340, 11-24.
- Viscarra Rossel, R., Behrens, T., Ben-Dor, E., Brown, D. J., Demattê, J. A. M., Shepherd, K. D., ... & Ji, W. (2016). **A global spectral library to characterize the world's soil.** *Earth-Science Reviews*, 155, 198-230.

Software

- General information on the EnMAP-Box, a free and open source python plugin for QGIS: https://www.enmap.org/data_tools/enmapbox/
- Download, documentation and tutorials of and with the EnMAP-Box: <https://enmap-box.readthedocs.io/>
- <https://artmoutilbox.com/>

Topic 4.2: Methods

- Angelopoulou, T., Balafoutis, A., Zalidis, G., & Bochtis, D. (2020). **From laboratory to proximal sensing spectroscopy for soil organic carbon estimation—a review.** *Sustainability*, 12 (2), 443.
- Angelopoulou, T., Chabrilat, S., Pignati, S., Milewski, R., Karyotis, K., Brell, M., Ruhtz, T., Bochtis, D. and Zalidis, G. (2023). **Evaluation of airborne HySpex and spaceborne PRISMA hyperspectral remote sensing data for soil organic matter and carbonates estimation.** *Remote Sensing*, 15, 1106. <https://doi.org/10.3390/rs15041106>

- Angelopoulou, T., Tziolas, N., Balafoutis, A., Zalidis, G., & Bochtis, D. (2019). **Remote sensing techniques for soil organic carbon estimation: A review.** *Remote Sensing*, 11 (6), 676.
- Chabrillat, S., Eisele, A., Guillaso, S., Rogaß, C., Ben-Dor, E., Kaufmann, H. (2011). **HYSOMA: An easy-to-use software interface for soil mapping applications of hyperspectral imagery.** 7th EARSeL SIG Imaging Spectroscopy workshop (Edinburgh, Scotland 2011).
- Gomez C., Drost A.P.A. and Roger J.-M. (2015). **Analysis of the uncertainties affecting predictions of clay contents from VNIR/SWIR hyperspectral data.** *Rem Sens Env.*, 156:58-70. <https://doi.org/10.1016/j.rse.2014.09.032>
- Peon, J., Recondo, C., Fernández, S., F. Calleja, J., De Miguel, E., & Carretero, L. (2017). Prediction of topsoil organic carbon using airborne and satellite hyperspectral imagery. *Remote Sensing*, 9 (12), 1211.
- Stenberg, B., Viscarra Rossel, R. A., Mouazen, A., & Wetterlind, J. (2010). **Chapter five – visible and near infrared spectroscopy in soil science.** *Advances in agronomy*, 107, 163–215.

Topic 4.3: Workflow

- Babet, A., Vu, P. V. H., Jacquemoud, S., Viallefont-Robinet, F., Fabre, S., Briottet, X., ... & Tian, J. (2018). **MARMIT: A multilayer radiative transfer model of soil reflectance to estimate surface soil moisture content in the solar domain (400–2500 nm).** *Remote Sensing of Environment*, 217, 1-17.
- Ben-Dor, E., Chabrillat, S., & Demattê, J. A. (2018). **Characterization of soil properties using reflectance spectroscopy.** In *Fundamentals, sensor systems, spectral libraries, and data mining for vegetation* (pp. 187-247). CRC press.
- Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T., & van Wesemael, B. (2019). **Imaging spectroscopy for soil mapping and monitoring.** *Surveys in Geophysics*, 40, 361-399.
- Demattê, J. A., Morgan, C. L., Chabrillat, S., Rizzo, R., Franceschini, M. H., Terra, F. D. S., ... & Wetterlind, J. (2015). **Spectral sensing from ground to space in soil science: state of the art, applications, potential, and perspectives.** *Land resources monitoring, modeling, and mapping with remote sensing*, 1, 647-708.
- Diek, S., Chabrillat, S., Nocita, M., Schaepman, M. E., & de Jong, R. (2019). **Minimizing soil moisture variations in multi-temporal airborne imaging spectrometer data for digital soil mapping.** *Geoderma*, 337, 607-621.
- Padarian, J., Minasny, B., & McBratney, A. B. (2019). **Using deep learning to predict soil properties from regional spectral data.** *Geoderma Regional*, 16, e00198.

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- Stenberg, B., Rossel, R. A. V., Mouazen, A. M., & Wetterlind, J. (2010). **Visible and near infrared spectroscopy in soil science.** *Advances in agronomy*, 107, 163-215.
 - Viscarra Rossel, R. A., McBratney, A. B., & Minasny, B. (Eds.). (2010). **Proximal soil sensing.** Springer Science & Business Media.

4.5 Quiz: Methodological aspects

Where can you get additional information on EnMAP data? (multiple-choice)

- By sending a fax to the German Aerospace Centre (DLR)
- From <https://www.enmap.org/>
- In this course
- From Guanter et al. 2015

What does the “A” in “Avisis NG” stand for? (single-choice)

- Average
- Airborne
- Advanced
- Avenger

If you want to visualize hyperspectral data, you can do this for FREE by using...
(multiple-choice)

- Code, e.g. R or Python
- Some GIS software, e.g. the free and open source QGIS
- Free QGIS plugins such as the EnMAP-Box
- Specific imaging spectroscopy software such as ENVI

Why is geometric correction important? (multiple-choice)

- Because it generates surface reflectance that provides a fingerprint of surface materials
- Because it transforms irregularly spaced image coordinates acquired in sensor geometry into regularly spaced pixels with a map projection
- Because it involves compensation for spatial non-uniformities (keystone effect), orthorectification and detector co-registration
- Because it involves compensation for spectral non-uniformities (smile effect)

Which different approaches to analyze spectral features do you know?

(multiple-choice)

- Computationally rather simple ones like narrow spectral indices
- More complex ones like parameterizing the features shape
- The modelling of absorption bands, for example Gaussian modeling
- The spectral angle mapper

Fill in the blanks

Spectral Feature Analysis is based on an **Choose an element** of the spectra with the samples. As you know, some soil properties **Choose an element**, causing absorption at a certain wavelength. The **Choose an element** of such a feature allows for the identification of the soil property that caused it, allowing for the direct retrieval of **Choose an element** information without the need for reference data!

A simple way to parameterize spectral features are narrow band indices. A more sophisticated way consists of analysing the actual shape of the feature, including for example ... (multiple-choice)

- Band and position
- Shoulder position
- Feature width
- Feature color
- Feature depth
- Feature area

Which approaches do belong to the category of statistical multivariate machine learning approaches? (multiple-choice)

- Multivariate statistical analyses such as Partial-least squares regression, PLSR for short
- Spectral feature analyses
- Machine learning algorithms such as random forest, artificial neural networks and support vector machines
- Radiative transfer modelling

State-of-the-art methods for the quantitative retrieval of soil properties are ... (multiple-choice)

- Spectral Feature Analyses, such as provided by the EnSoMAP toolset in the EnMAP-Box
- Radiative transfer modelling approaches
- Statistical multivariate machine learning approaches
- Spectral Mixing Analyses also known as Linear Spectral Unmixing, used among other methods to detect Fractional coverage of green vs dry vegetation vs soils

Identify methods used to prepare spectral data for the application of soil specific algorithms: (multiple-choice)

- Careful inspection of spectra for “spikes” that the algorithms may misinterpret as “features”
- Smoothing, e.g. Savitzky-Golay
- Removal of bands, for example in the spectral atmospheric water absorption ranges
- Normalizations, for example “continuum removal”
- Data transformations, for example derivatives or absorbance
- Dimensionality reduction, for example Minimum Noise Fraction Transformation or Principal Component Analysis
- Cosmetic correction
- Masking of any pixels that are not bare (or at least semi bare) soil

5 Hands-On training

Welcome to our hands-on lesson! You can actively participate in the following topics – some of the exercises were designed specifically for this course! Both the software and the data can be downloaded for free and we will guide you step by step. Installation of the EnMAP-Box and active participation in any tutorial are not compulsory to pass this MOOC, however, for the best learning outcome we strongly encourage you to use this opportunity to “get your hands dirty” with some expert-guided hands-on training exercises! As before, Charly will explain the learning objectives of this – final – lesson in the video below.

VIDEO: Soil-08: Imaging Spectroscopy for Soil Applications: Lesson 03 Intro



URL of the video: <https://youtu.be/b36BGIFQznE>

Let's move on with the first topic of this lesson!

5.1 Introduction to the EnMAP-Box

As Charly just explained, we will be using the EnMAP-Box “Soil Applications” as well as the “Regression workflow” toolsets to learn how to retrieve quantitative geochemical soil information from hyperspectral data. In case you already have the EnMAP-Box installed and are familiar with the visualization tools, you can skip this topic. For everyone else, we have produced the **following two screencasts to provide an introduction to working with the EnMAP-Box**. The first screencast explains the **installation of the EnMAP-Box software** and the second the **different visualization tools**. For detailed and up-to-date information on the EnMAP-Box please visit the [documentation website](#), where you can also find a user manual as well as several application tutorials. Please refer to the installation website for information on the [latest supported QGIS version](#).

Installation

VIDEO: Basic-22: Hands-on training: EnMAP-Box Installation



URL of the video: <https://youtu.be/SNbLmB8aCQ>

Data visualization

VIDEO: Basic-24: Hands-on training: EnMAP-Box Spectral Library



URL of the video: <https://youtu.be/qVoi0Cojhel>

Quiz: Introduction to the EnMAP-Box

In the EnMAP-Box, you can visualize the following data types (multiple-choice)

- Raster data
- Vector data
- Spectral libraries
- Exclusively EnMAP data but in all levels (L1B, L1C, L2A)

The EnMAP-Box is a great tool for hyperspectral data visualization and analyses ... (multiple-choice)

- ... as you can easily select which bands to combine in an RGB view of an image
- ... as image and vector data can be displayed together in the same “map view” panel
- ... as several “map view” panels can be spatially linked in side-by-side representations
- ... as spectral pixel information can be displayed as spectral profiles in a separate “spectral library” window

5.2 EnMAP-Box hands-on training exercises

Okay, here we go. In the following three screencasts, we will show you step-by-step how to get acquainted with the data and apply the EnSoMAP 2.0 module. The EnSoMAP module is based on the HYSOMA algorithms (Chabrilat et al. 2016) and allows the fully automatic generation of semi-quantitative soil maps for soil moisture, soil organic matter, iron oxide, clay, and carbonate content, and includes quantitative soil mapping tools. Thus, EnSoMAP provides non-expert users with a set of tools which can be used for soil applications by incorporating modern hyperspectral algorithms with an easy-to-use graphical interface based on simple menu-driven functions. It includes a soil mask option to remove water, green and dry vegetation pixels based on spectral indices. In order to create semi-quantitative soil maps based on analytical and empirical algorithms no user input data (e.g. spectral libraries, ground truth data) is needed. Moreover, EnSoMAP offers the choice of multiple algorithms for each soil parameter. For more experienced users there are additional tools that allow for a fully quantitative soil mapping.

For active participation, you can **download the data** here.

- [Demmin, Germany \(2015\) – a \(hyperspectral\) dataset for active participation in the HYPERedu MOOC on soil applications](#)
- [Cabo de Gata-Níjar Natural Park, Spain \(2005\) – a \(hyperspectral\) dataset for active participation in the HYPERedu MOOC on soil applications](#)

Getting acquainted with the data (feature analysis tutorial)

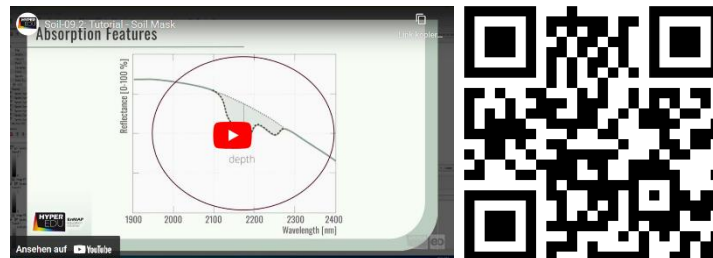
VIDEO: Soil-09.1: Tutorial – Data



URL of the video: <https://youtu.be/9a1VIsen5Y8>

Applying soil masks and calculating soil property maps (feature analysis tutorial)

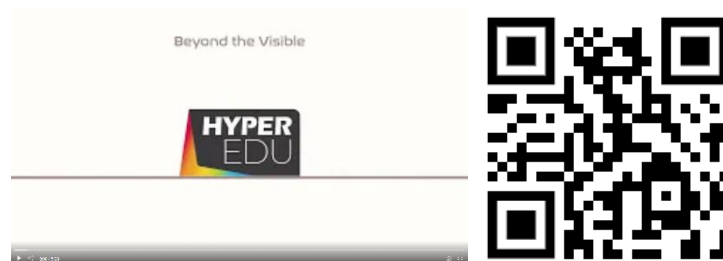
VIDEO: Soil-09.2: Tutorial – Soil Mask



URL of the video: <https://youtu.be/ljd6zUgcm74>

Validating quantitative maps (feature analysis tutorial)

VIDEO: Soil-09.3: Tutorial – Validation



URL of the video: <https://youtu.be/OsifnukAvWE>

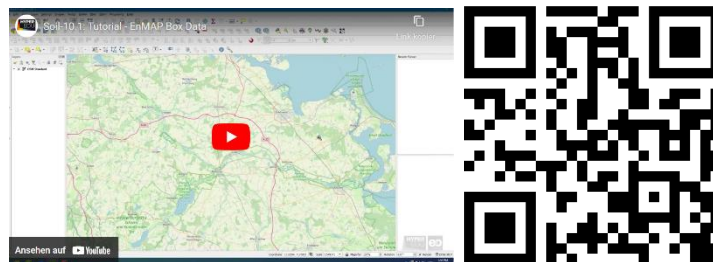
Are you wondering why we are still working with airborne data when EnMAP has been acquiring data for more than a year at date? Believe it or not, we were super excited to **finally** work and teach with real EnMAP data – but then, well, reality happened. The seasons in which acquisitions of **dry bare soil** are possible are very limited to early spring and late summer/early autumn in most European regions – in between, the soil is covered by green vegetation (summer) or the sun elevation angle is too low (winter) ... and then, there is cloud cover. Besides, it's not like EnMAP is hovering over our study sites, waiting for perfect conditions, additionally considering competing acquisitions. Frustratingly, we did not get a good EnMAP acquisition of our study site Demmin, Northern Germany at date of publishing this MOOC! In combination with restrictions on ground reference data availability (including permission to publically

share them with the world) and the time it takes to design and thoroughly test an exercise, we (and thus you) are still stuck with the good old airborne data ... nevertheless, we are looking forward to providing you with a revised version of this MOOC, including real EnMAP data somewhen in the future!

In any case, we can learn a lot by using airborne data, so we will be using the EnMAP-Box regression workflow in our next tutorial, which is suited to quantify soil organic carbon (SOC) from HySpex data over Demmin, where SOC is excitingly variable.

Getting acquainted with the data (regression tutorial)

VIDEO: Soil-10.1: Tutorial – EnMAP Box Data



URL of the video: <https://youtu.be/RZBCyS4t3vk>

Calculating and validating soil property maps (regression tutorial)

VIDEO: Soil-10.2: Tutorial – EnMAP Box Data SOC Map



URL of the video: <https://youtu.be/JXVR16JE4ek>

Quiz: EnMAP-Box hands-on training exercises

In the exercises, we are working with scenes acquired by which sensors?

(multiple-choice)

- HyMAP
- AVIRIS
- EnMAP
- HySpex
- AVIRIS-NG

In the EnSoMAP tutorial, we applied a mask to exclude all pixels that do not represent (mostly) bare soil. The masks were derived from a combination of indices, namely ... (multiple-choice)

- Normalized Difference Vegetation Index – NDVI (to identify green vegetation)
- Normalized Difference Vegetation Index – NDVI (to identify dry vegetation)
- Normalized Cellulose Absorption Index – NCAI (to identify dry vegetation)
- Normalized Difference Red Blue Index – NDRBI (to identify water)
- Normalized Difference Soil Index – NDSI (to identify pure soil pixels)

Which models were used in the regression workflow tutorial? (multiple-choice)

- A generic regressor
- A PLSR regression
- A RandomForestRegressor
- A Linear Regression
- A GaussianProcessRegressor

5.3 Discussion of accuracy and limitations

In the previous exercises, we retrieved quantitative information from hyperspectral images and validated our result using some in-situ measurements.

How accurate are the in-situ measurements?

Well, there are several aspects to consider. Most importantly, our ground reference data is not entirely “true” as some variables are highly variable in space and time and we only collected a very limited number of samples. And despite our best efforts, errors may happen in the lab during sample analyses. Therefore, we refer to in-situ data oftentimes as ground reference rather than ground truth data.

Consideration of differences between in-situ and airborne data

With regard to the accuracy of in-situ measurements addressed above ... how accurate is their location? Many GPS devices return spatial accuracies around 5 m, which is in the range of one pixel difference in location. Bearing in mind that the geolocation of a pixel might not be 100% accurate, there can easily be an offset between the ground information and what seems to be the corresponding pixel!

Then, the spatial scale in the field is different from airborne (or even spaceborne) resolution: The hyperspectral instrument observing the soil surface from above integrates the signal across an area of several meters according to its point spread function while the field samples resemble point measurements, even if several samples per reference site are collected and averaged.

In addition to differences in this “horizontal” scale, any VNIR-SWIR sensor can only “see” the very top of the soil, while reference samples usually contain several centimeters of soil in depth. This may be negligible in agricultural soils which are regularly ploughed and thus mixed. However, in more “natural” soils, concentrations of constituents may differ.

When the spectral signals are mixtures of soil properties – do we need reference measurements then?

Well, if they are so hard to compare, should we even work with reference data? In cases where no reference data are available, we can still produce semi-quantitative maps, e.g. using the feature analyses approach. Alternatively, regression models or machine learning algorithms can be trained with reference data from sources like spectral libraries. However, these models are trained on laboratory spectra and at present cannot be transferred to air- or spaceborne scale. There are currently

investigations how large scale soil spectral libraries can be used. Thus, for regression and/or machine learning approaches we really need soil properties information from the study site.

Validation or quantification of uncertainties

In our exercises, we quantified **uncertainties** that indicate the deviations of retrieval products from “hypothetically true” values collected in-situ during ground campaigns. This is pretty straightforward. Check the model metrics and plot modelled versus measured values.



Our experience

- If in-situ data are available, they should be used – for training or at least for validation purposes
- If the number of reference data is high, you can split them into a training and an independent validation dataset. However, if the number of samples is limited, use a cross validation option. How many samples are needed exactly as a minimum depends on the study site and its variability as well as the applied method of analysis. PLSR and Random Forest can cope with a little number of samples though more are usually advisable.
- Try to make sure that the reference or in-situ data used to train your model covers the entire range of values to be expected – for example, don't train a model with SOC samples ranging 1-3 g/kg when you want to apply the model to an image where you expect areas with 30 g/kg of SOC.
- Check the model metrics, the root mean squared error (RMSE), the RPD value and the coefficient of determination (R^2), for instance. There are few "hard thresholds" but you can expect higher R^2 and lower RMSE for laboratory than for airborne or even spaceborne data. One threshold that is accepted in the soil spectroscopy community is that of the RPD exceeding 1.4 – if the value is lower, the model is likely not to be trustworthy.
- Check the deviations of modelled values from the values of in-situ samples, for example in scatter plots. Is there a systematic under- or over-prediction for e.g. higher or lower values? This might be due to the samples with higher values of a certain soil property being under-represented or due to detection limits if the content of a soil property is too low.

Quiz: Discussion of accuracy and limitations

Which differences between in-situ and airborne data do we have to consider?

(multiple-choice)

- Differences in spatial scale of data acquisition
- A VNIR-SWIR sensor can only “see” the very top of the soil while reference samples usually contain several centimeters of soil in depth
- In situ data are always correct while spectral data are less accurate

How can we assess the quality of our results? (multiple-choice)

- By checking the model metrics, e.g., the root mean squared error (RMSE) and the coefficient of determination (R^2)
- By checking the pickle file produced by the EnMAP Box
- By checking the deviations of modelled values from the values of in situ samples, e.g. in scatter plots
- By adapting the color scales used to display soil property maps

5.4 Resources section: 'Hands-On training'

In this section, we have assembled resources used for the creation of this lesson that we recommend for further reading as they provide a lot more detail on the different topics. Please remember that this selection is not a complete overview of all resources – if you think an important resource is missing, let us and your fellow students know (e.g. in the discussion forum).



Sources and further reading

Topic 1: Introduction to the EnMAP-Box

- General information on the EnMAP-Box, a free and open source python plugin for QGIS: https://www.enmap.org/data_tools/enmapbox/
- Download, documentation and tutorials of and with the EnMAP-Box: <https://enmap-box.readthedocs.io/>

Topic 2: EnMAP-Box Soil Applications

- <https://enmap-box.readthedocs.io/en/latest/>

Topic 3: EnMAP-Box Regression workflow

- General information on the “regression workflow” toolbox and guidance on how to apply the tool: https://enmap-box.readthedocs.io/en/latest/usr_section/usr_manual/applications.html#regression-workflow-deprecated

Topic 4: Discussion of accuracy and limitations

- Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T., & van Wesemael, B. (2019). **Imaging spectroscopy for soil mapping and monitoring**. *Surveys in Geophysics*, 40, 361-399
- Angelopoulou et al. (2019). **Remote Sensing Techniques for Soil Organic Carbon Estimation: A Review**. *Remote Sensing*. 11, 676; doi:10.3390/rs1106067

6 Goodbye!

Yippieh – well done! You've learned a lot about imaging spectroscopy for soil applications. Let's get to our **final survey!** The survey helps us as a team to improve this as well as future courses and will take you about 2 minutes. Afterwards it will get serious...we want to test your knowledge with the Final Exam!

6.1 Final User Survey

Thank you for taking the time to answer our final survey! We are aiming to regularly review your answers and update the course accordingly. If you have any further suggestions, please let us know via email or through the discussion forum. You can access the [Link](#) to this course once you have enrolled to it.

6.2 Final Exam

Here we go, below you will find the final exam. If you've paid close attention in the previous lessons, you should be able to answer them easily. But even if you haven't, you have unlimited attempts to pass so don't get nervous!

Fill in the blanks

In general, increases in particle size cause a **Choose an element** in overall reflectance. Also, reflectance generally decreases with **Choose an element** organic matter and/or moisture content.

Since the major constituents of soil minerals (O, Si, Al, and Mg) do not exhibit absorption features in the VNIR and SWIR range, soil spectral reflectance characteristics are mainly influenced by ... (multiple-choice)

- ... iron-oxide content
- ... clay mineral composition
- ... organic matter content
- ... texture and surface roughness
- ... salinity
- ... moisture content
- ... dry vegetation residues

Dry vegetation and bare soil can be distinguished best based on... (single-choice)

- ... the cellulose absorption feature around 2100 nm
- ... the cellulose absorption feature between 700 and 1300 nm
- ... their water content

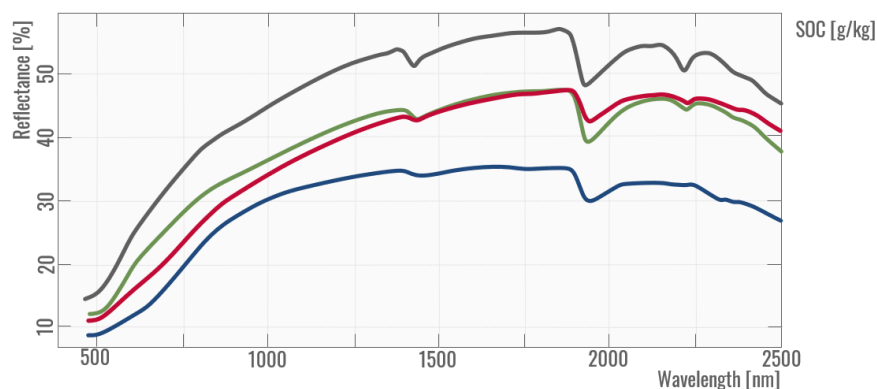
Fill in the blanks

Chemical chromophores are substances that **Choose an element**, leading to diagnostic absorption features for certain materials. Everything **Choose an element** is considered a **physical chromophore**.

Please select only the chemical chromophores: (multiple-choice)

- Soil minerals
- Soil particle size
- Viewing geometry
- Soil organic matter
- Soil salinity
- Surface roughness
- Soil crusts
- (to some extent) Soil water
- Radiation intensity

Rank the different soils in the order of their SOC (soil organic carbon) content (start with the lowest).



Choose an element

Choose an element

Choose an element

Choose an element

With respect to soil properties, what are “primary variables”? (multiple-choice)

- Variables that are most important for soil applications
- Variables that are directly involved in radiative transfer mechanisms
- Variables that are not directly related to the radiative transfer mechanisms
- Variables that can be inferred directly from imaging spectroscopy data

What do you need to consider when collecting soil spectra in the field?

(multiple-choice)

- To allow sufficient instrument warm-up time
- To wear dark clothes
- To look out for overpassing satellites
- To avoid bright or reflecting surfaces near the target
- To not cast a shadow on anything you want to measure
- To stick to bare soil areas, preferably in the middle of the field
- To wear a hat
- To measure under stable illumination conditions
- To repeat white reference and, if necessary, optimization
- To always keep notes on everything

State-of-the-art methods for the quantitative retrieval of soil properties are ...

(multiple-choice)

- Spectral Feature Analyses, such as provided by the EnSoMAP toolset in the EnMAP-Box
- Radiative transfer modelling approaches
- Statistical multivariate machine learning approaches
- Spectral Mixing Analyses also known as Linear Spectral Unmixing, used among other methods to detect Fractional coverage of green vs dry vegetation vs soils

What are the advantages of spectral feature analyses? (multiple-choice)

- They allow for the semi-quantification of soil geochemical and -physical properties without the need for any calibration data
- With in-situ information, even absolute quantification is possible
- The spectral feature analysis is the most accurate technique and highly transferable between different ecoregions
- The spectral feature analysis is often quite robust and easy to apply

Identify methods used to prepare spectral data for the application of soil specific algorithms: (multiple-choice)

- Careful inspection of spectra for “spikes” that the algorithms may misinterpret as “features”
- Smoothing, e.g. Savitzky-Golay
- Removal of bands, for example in the spectral atmospheric water absorption ranges
- Normalizations, for example “continuum removal”
- Data transformations, for example derivatives or absorbance
- In-situ measurements, e.g. of one or several soil geochemical properties
- Dimensionality reduction, for example Minimum Noise Fraction Transformation or Principal Component Analysis
- Cosmetic correction
- Masking of any pixels that are not bare (or at least semi bare) soil

Which different approaches to analyze spectral features do you know?

(multiple-choice)

- Computationally rather simple ones like narrow spectral indices
- More complex ones like parameterizing the features shape
- The modelling of absorption bands, for example Gaussian modeling
- The spectral angle mapper

In the EnMAP-Box, you can visualize the following data types (multiple-choice)

- Raster data
- Vector data
- Spectral libraries
- Exclusively EnMAP data but in all levels (L1B, L1C, L2A)

In the EnSoMAP tutorial, we applied a mask to exclude all pixels that do not represent (mostly) bare soil. The masks were derived from a combination of indices, namely ... (multiple-choice)

- Normalized Difference Vegetation Index – NDVI (to identify green vegetation)
- Normalized Difference Vegetation Index – NDVI (to identify dry vegetation)
- Normalized Cellulose Absorption Index – NCAI (to identify dry vegetation)
- Normalized Difference Red Blue Index – NDRBI (to identify water)
- Normalized Difference Soil Index – NDSI (to identify pure soil pixels)

Which differences between in-situ and airborne data do we have to consider?

(multiple-choice)

- Differences in spatial scale of data acquisition
- A VNIR-SWIR sensor can only “see” the very top of the soil while reference samples usually contain several centimeters of soil in depth
- In situ data are always correct while spectral data are less accurate

6.3 Goodbye

Thank you for completing the entire MOOC on hyperspectral remote sensing for soil applications! We hope you had as much fun participating as we did creating this course (and a comparably steep learning curve) and that you will become an active member of the hyperspectral community! You know, the data is complex and we need a lot of experts ...



We prepared a little treat for you – check the interactive picture below to learn some fun facts about your course instructors!

When on a field trip in the Namibian Kalahari, the excursion group suffered a flat tyre - while fixing it, a small tornado crossed the landscape only a few meters away from the group. A magnificent view!

... has a glass jar at home that shows the soil profile from the ground level to a depth of 70 metres right below the house.

Chris was a little horrified when during his very first "soil" excursion, he experienced that sheep droppings (like many other organic materials) do actually NOT degrade in turf soils ... even after very long time periods



We were in Demmin to take soil samples. Of course, we had determined the sampling locations beforehand and then navigated on site using a GPS device. It had rained a lot in the days before. With my eyes fixed on the GPS device, I walked into a puddle that turned out to be a temporary lake on a field... We briefly considered taking a sample underwater, but then decided to rather move the sampling location spontaneously.

If you still want to learn more, check out the resource sections of the lessons where we have tried to link a lot of extra material and further reading. If you want to practice, download EnMAP data, install the EnMAP-Box (if you haven't done so yet) and check out the other tutorials. Also, stay tuned for our follow-up MOOCs on specific applications



MOOC Document

Beyond the Visible – Imaging Spectroscopy for Soil Applications

Version: 1.0 (Course Version 1.0)

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