MOOC Document

Beyond the Visible – Imaging Spectroscopy for Agricultural Applications

Acknowledgements

Version: 1.0 (Course Version 1.0)

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List of Abbreviations

The list includes all terms that are introduced in the MOOC

ALIA: Average leaf inclination angle

ALG: Atmospheric Look-up Generator

ANN: Artificial neural network

ARTMO: Automated Radiative Transfer Models Operator (Toolbox)

ASD: Analytical Spectral Devices

ASI: Italian Space Agency

ASI: Analyze Spectral Integral (part of EnMAP-Box Agri-tools)

AVIRIS-NG: Airborne Visible Infrared Imaging Spectrometer – Next Generation

BBCH: Scale used to identify the phenological development stages of a plant

BRDF: Bidirectional Reflectance Distribution Function

Cab: Chlorophyll A + B

Cant: Leaf anthocyanin content

CBC: Carbon-based leaf constituents

CHIME: ESA's Copernicus Hyperspectral Imaging Mission of the Environment

Cp: Leaf protein

CR: Crop residue

CWC: Canopy water content

Cw: Water content

Cxc: Leaf carotenoid content

DART: Discrete anisotropic radiative transfer (3D radiative transfer model)

DATimeS: Decomposition and Analysis of Time Series software

EeTeS: EnMAP end-to-end simulator

EnMAP: Germany's Environmental Mapping and Analysis Program

EM: Endmember

EWT: Leaf water content (also referred to as CW)

fAPAR: Fraction of absorbed photosynthetically active radiation

FVC: Fractional vegetation cover (also referred to as fCOVER)

GFZ: German Research Center for Geosciences (Potsdam)

GIS: Geographic Information System

GPP: Gross primary productivity

GPR: Gaussian process regression

GSA: Global sensitivity analysis

IVVRM: EnMAP-Box tool for interactive visualization of vegetation reflectance models

LAD: Leaf inclination angle distribution

LAI: Leaf area index

LCC: Leaf chlorophyll content

LMA: Leaf mass per area

LMU: Ludwig-Maximilians-Universität München

LUT: Look up table

MIR: Mid infrared

MOOC: Massive open online course

N: Nitrogen

NADPH: Nicotinamide adenine dinucleotide phosphate

NIR: Near-infrared

NPV: Non-photosynthetic vegetation

PCA: Principal Component Analysis

PRISMA: PRecursore IperSpettrale della Missione Applicativa

PROSAIL: Combined PROSPECT + SAIL model

PROSPECT: Leaf optical properties model

RTM: Radiative Transfer Model

SAIL: Canopy bidirectional reflectance model

SBG: NASA's Surface Biology and Geology Investigation Mission

SCOPE: Soil Canopy Observation, Photochemistry and Energy fluxes (model)

SD: Standard deviation

SIF: Sun-induced fluorescence

SWIR: Short wave infrared

TIR: Thermal infrared

UV: Ultraviolet

USGS: United States Geological Survey

VIS: Visible (light)

VNIR: Visible near-infrared

1 Welcome

Hi there, welcome to the Massive Open Online Course (MOOC) ‚***Beyond the Visible – Imaging Spectroscopy for Agricultural Applications***'!

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

The first lesson is accessible to everyone – here, you can meet your instructors and they will explain the benefits of hyperspectral over other types of remote sensing data, as well as the challenges and opportunities for applications in an agricultural context. Plus, you will get a glimpse of 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 basics of hyperspectral remote sensing that you need to pass to access 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 to fifth lesson comprise the actual content and will introduce you to the (theoretical) background of vegetation reflectance including which "traits" or variables can be retrieved from hyperspectral imagery, followed by some methodological considerations for agricultural applications. In the final lesson, you'll get the chance to participate in 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**. In each final 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 document!** You have **unlimited attempts to pass for all quizzes**.

> This offline version of the MOOC on agricultural applications enables everyone to access the content of such – however, in order to successfully complete the course, one must necessarily pass each of the quizzes as well as the final exam. For acquiring the certificate of completion, you need to pass the lesson quizzes, as well as the final assessment online.

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

- the benefits of imaging spectroscopy for agricultural applications
- the physical and chemical factors controlling leaf and canopy reflectance
- which biophysical and biochemical variables can be retrieved as "vegetation traits"
- some basics of campaign- and sampling design
- how reference data are acquired in an agricultural context
- where you can get imaging spectroscopy data from and what software you can use
- which methods to apply in an agricultural context
- and finally, how to analyze an imaging spectroscopy dataset yourself!

💡

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 smart phone as well. For the best learning experience, we recommend to participate 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.

VIDEO: Agri-01: Imaging Spectroscopy for Agricultural Applications - Welcome!
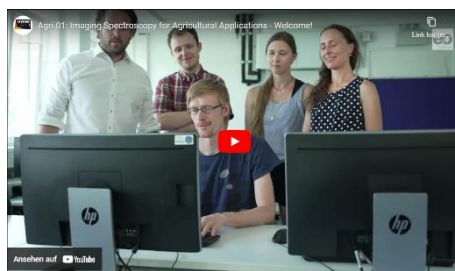
URL of the video https://youtu.be/Z04I71-_DJo

1.1 Hyperspectral remote sensing for agricultural monitoring

In the face of a growing world population, global agriculture faces numerous challenges, including the production of sufficient food, fibre and energy from limited resources. Spaceborne imaging spectroscopy offers highly relevant data for monitoring vegetation status and dynamics, which are needed for various applications in agriculture, ranging from the field to global scale.

"Humankind is facing an unprecedented challenge to produce enough food for the coming decades due to population growth and increase in the average demand per capita, changes in climate conditions, and limitations in arable land area, as well as pressure on the water and resources." (Ninomiya et al., 2019)

To meet this **increasing food demand**, more land needs to be converted to arable land or the use of existing land has to be intensified and/or genetics of crops improved. However, the conversion to arable land comes at the expense of other types of land use, such as forests, which benefit biodiversity and act as carbon sinks. Agriculture causes almost 12 % of global greenhouse gas emissions (according to IPCC 2014), significantly contributing to climate change.

Climate change leads to global warming, increasing variability in seasonality, changes in rainfall patterns and increases in extreme weather events such as heatwaves, drought, storms and floods. Consequently, the agricultural sector is expected to face changes in crop and livestock viability, new pests, pathogens, and weed problems due to climate change. Climate adaptation is currently one of the biggest challenges to sustainability! (Minoli et al., 2019)

In order to ensure a **sustainable food supply** for a growing world population, informed agricultural management is necessary. Major impacts on agricultural production come from **managing the most important production factors, namely nutrient and water supply**. The use efficiency of production
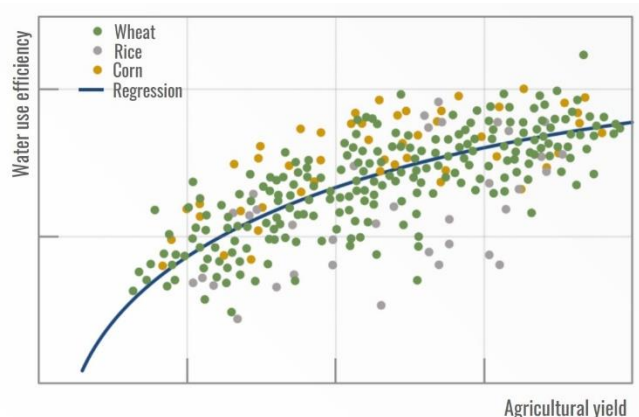
Figure 1 **Relationship between Water use efficiency and agricultural yield**.
Berger et al. (2021): Spaceborne Imaging Spectroscopy of Agricultural Systems (HYPEREdu slide collection)

factors, such as water use efficiency, increases with higher yield levels that are associated with mechanized and information-driven cultivation.

If properly implemented, agriculture can positively contribute to ecosystem services (Power 2010), including but not limited to, the regulation of soil and water quality, carbon sequestration, support for biodiversity and cultural services. However, if not properly implemented, agriculture can be associated with severe environmental problems, such as the loss of wildlife habitat, nutrient runoff, sedimentation of waterways, greenhouse gas emissions or pesticide poisoning of humans and non-target species.

Some of the negative impacts of agriculture can be traced back to a limited understanding of land surface heterogeneity. Thanks to its extensive spatial sampling capabilities, **remote sensing** can contribute to addressing existing knowledge-gaps and assist in implementing agricultural practices that fully take the natural heterogeneity of the land surface into account. The practice of optimizing agricultural production based on measurements of temporal and spatial land surface dynamics is summarized under the term **precision** or **smart farming**. Smart farming can improve yield of existing bio-productive surfaces, while simultaneously increasing the use efficiency of production factors, such as water and nutrients.

Smart farming is highly dependent on information derived from satellite (and drone) technology: "Remote sensing data can greatly contribute to the monitoring task by providing timely, synoptic, cost efficient and repetitive information about the status of the Earth's surface" (Atzberger, 2013).

Today, a **new generation of spaceborne imaging spectroscopy missions** is underway, which will enable the regular estimation of more challenging traits, such as pigments, nitrogen content and non-photosynthetic vegetation. Hence, these missions will **provide enhanced understanding of underlying physiological processes of functional traits**.

> 💡 ### Why should we prefer hyperspectral sensors over multispectral systems?
>
> Ustin & 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…"
>
> „High-frequency monitoring of agriculture will increase the likelihood of obtaining timely data throughout a growing season, especially at critical developmental stages in a crop life cycle or when affected by environmental stresses (e.g., drought or disease)."

In summary, there is a range of agricultural applications that can be supported by spaceborne hyperspectral remote sensing, e.g., monitoring vegetation status and dynamics, nutrient and water status, crop evapotranspiration, pest and disease infestation, crop yields, as well as production forecasting and precision agriculture.

While a few of these applications are already operational, some are still under development. However, for all these applications, crop characteristics or functional vegetation traits need to be derived from hyperspectral data.

For our MOOC "Beyond the Visible – Introduction to Hyperspectral Remote Sensing" PD Dr. Tobias B. Hank (Ludwig-Maximilians-Universität München, Department of Geography) summarized the advantages and current challenges of hyperspectral remote sensing in the context of agricultural applications in an interview.

Video: Basic-04: Expert interview: application field "agriculture"

URL of the Video: https://youtu.be/DaZF3jRnMfs

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.

1.2 EnMAP – The German Spaceborne Imaging Spectroscopy Mission

The **Environmental Mapping and Analysis Program (EnMAP) is a German hyperspectral satellite mission** that aims at monitoring and characterizing Earth's environment 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 DLR Space Agency with resources from the German Federal Ministry for Economic Affairs and Climate Action and 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 share our knowledge with all potential users of hyperspectral data and encourage the growth of a global imaging spectroscopy community.

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

Video URL: https://youtu.be/LQZNtLp3RfM

1.3 Resources

In this section, we have assembled resources used for the creation of this lesson that we recommend you use 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).

You can find most figures of this lecture in the HYPERedu slide collection, available on EO-College.

How to cite: K. Berger, M. Weiss., S. Steinhauser, J. Verrelst, C. Atzberger, G. Tagliabue, T. Hank, M. Wocher, T. Kuester, S. Foerster (2021). **Spaceborne Imaging Spectroscopy of Agricultural Systems**, HYPERedu, EnMAP education initiative, May 2021, LMU Munich.

Available in the **EO-College hyperspectral resources section** under: https://eo-college.org/resource/spaceborne-imaging-spectroscopy-of-agricultural-systems/

Hyperspectral remote sensing for agricultural monitoring

State-of-the-art publications

Atzberger 2013: **Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs**. Remote sensing 5 (2), 949-981.

Hank T., Berger K., Bach H., Clevers J.G.P.W., Gitelson A., Zarco-Tejada P., Mauser W. (2019): **Spaceborne Imaging Spectroscopy for Sustainable Agriculture: Contributions and Challenges**. Surveys in Geophysics. 40, 515-551. https://doi.org/10.1007/s10712-018-9492-0

Lu, B., Dao, P.D., Liu, J., He, Y., Shang, J. (2020): **Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture**. Remote Sens. 12, 2659. https://doi.org/10.3390/rs12162659

Park, B., & Lu, R. (Eds.). (2015). **Hyperspectral imaging technology in food and agriculture (Vol. 1)**. New York: Springer.

Ustin, S.L., & Middleton, E.M. (2021): **Current and near-term advances in Earth observation for ecological applications**. Ecological Processes, 10, 1. https://doi.org/10.1186/s13717-020-00255-4

Verrelst, J., Malenovský, Z., Van der Tol, C., Camps-Valls, G., Gastellu-Etchegorry, J.-P., Lewis, P., North, P., & Moreno, J. (2019): **Quantifying Vegetation Biophysical Variables from Imaging Spectroscopy Data: A Review on Retrieval Methods**. Surveys in Geophysics, 40, 589-629. https://doi.org/10.1007/s10712-018-9478-y

Weiss, M., Jacob, F., & Duveiller, G. (2020): **Remote sensing for agricultural applications: A meta-review**. Remote Sensing of Environment, 236, 111402. https://doi.org/10.1016/j.rse.2019.111402

Further publications mentioned in text

IPCC, 2014: **Climate Change 2014: Synthesis Report**. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Minoli, S., Müller, C., Elliott, J., Ruane, A.C., Jägermeyr, J., Zabel, F., Dury, M., Folberth, C., François, L., Hank, T., Jacquemin, I., Liu, W., Olin, S., & Pugh, T.A.M. (2019). **Global Response Patterns of Major Rainfed Crops to Adaptation by Maintaining Current Growing Periods and Irrigation**. Earth's Future, 7, 1464-1480

Ninomiya, S., Baret, F., & Cheng, Z.-M. (2019). **Plant Phenomics: Emerging Transdisciplinary Science**. Plant Phenomics, 2019, 2765120

Power, A.G. (2010). **Ecosystem services and agriculture: tradeoffs and synergies**. Philosophical Transactions of the Royal Society B: Biological Sciences, 365, 2959-2971

EnMAP – The German Spaceborne Imaging Spectroscopy Mission

www.enmap.org

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. **The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation**. Remote Sens. 2015, 7, 8830-8857. https://doi.org/10.3390/rs70708830

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!

Quiz: The 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
- MIR
- UV
- NIR
- SWIR
- VIS
- Microwaves
- TIR

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 is very cheap to acquire

☐ 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

☐ Greem 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 agricultural applications

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

Video: Agri-02: Imaging Spectroscopy for Agricultural Applications - Lesson 3 Intro

Video URL: https://youtu.be/bgIyKl4R3vs

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

3.1 Imaging spectroscopy of vegetation (for agricultural applications)

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 into 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** occurs on the cell walls within the cells, at chloroplasts and other cell organelles and especially in the air-filled intercellular spaces.
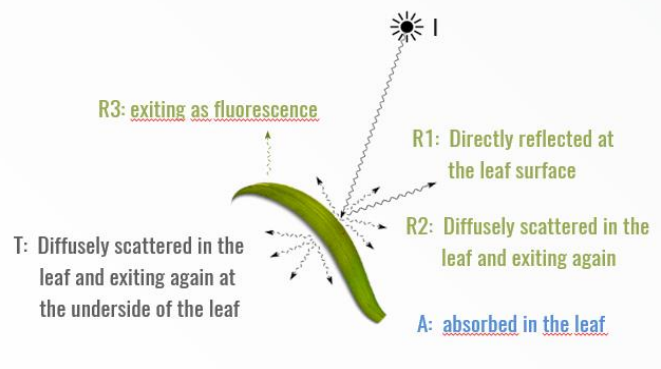
Figure 2 **Interaction of radiance with leaf.** Adapted from Berger et al. (2021) Spaceborne Imaging Spectroscopy of Agricultural Systems (HYPERedu slide collection)
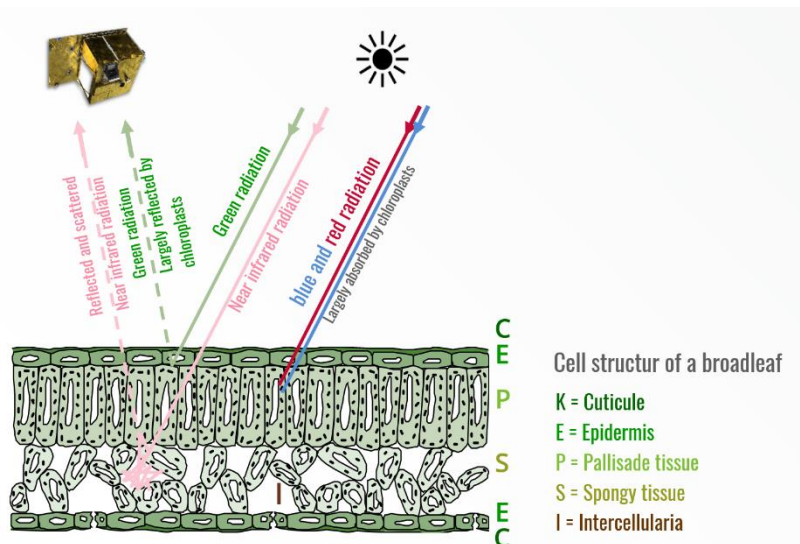
Figure 3 **Leaf cell structure.**
Figure in courtesy of Theres Kuester; Illustration of the EnMAP satellite with permission from DLR Space Administration

In addition to the complex interaction at the leaf level, **the interaction with radiance occurs at three scales**:

Figure 4 **Interaction with incoming radiation at three scales.**
Figure reprinted from Kuester et al. (2014) with permission from IEEE
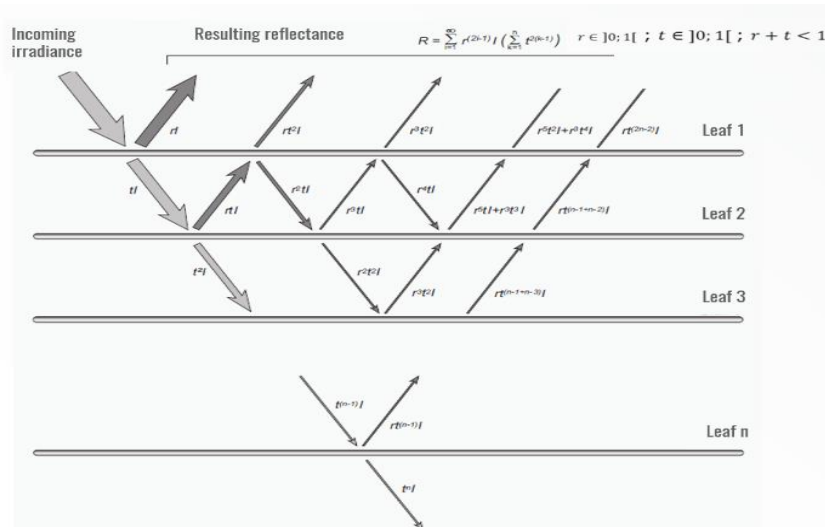
Figure 5 **Effect of multiple leaf layers.**
Figure in courtesy of Theres Kuester

In nature, we rarely deal with single leaves but entire plants and therefore need to consider the effect of several leaf layers. The leaf surface is the decisive size (determined by the leaf area index, LAI).

With increasing LAI, reflectance decreases in the visual wavelength range due to absorption by leaf pigments and increases in the NIR wavelength range due to scattering by leaf and plant structure. **Radiation that passes through several leaf layers adds to the effects of absorptance, reflectance and transmittance**. Therefore, above a certain number of leaf layers, saturation occurs (which can be a limitation for the derivation of LAI from remote sensing data).

Now, in remote sensing, we often deal with several plants that are forming vegetation stands or canopies. They are characterized by the morphology of plants and phytoelements, the phenology and vitality of individual plants, the arrangement and

density of the plants, the composition of plant species (natural vs. cultivated vegetation) as well as the geometry and reflectivity of soil background.
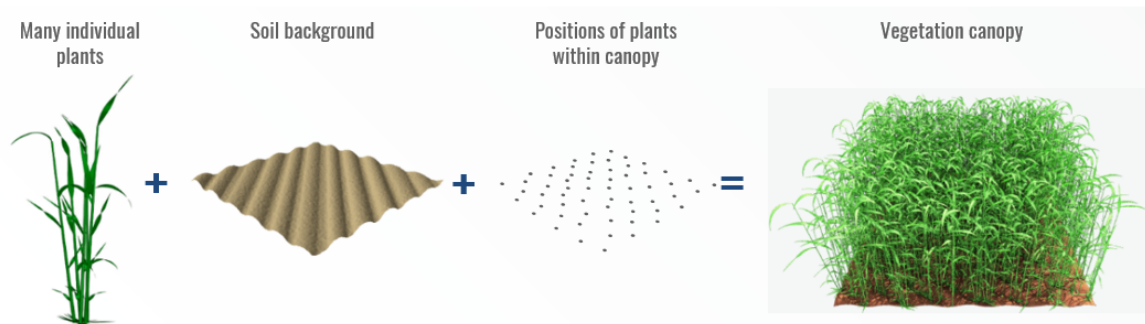
Figure 6a **Structure of a vegetation stand.**
Figure reprinted from Kuester et al. (2014) with permission from IEEE

Overall, **absorption characteristics of green vegetation are predominantly similar**, even between plant species, because the molecular mechanisms underlying absorption are found in all plants (for example, O-H bond in water, cellulose and starch). Therefore, clear assignments of absorption bands and molecular processes are difficult to make. Except for the leaf pigments (e.g. chlorophyll and carotenoids), many biochemical plant substances occur in low concentrations, so that only minimal absorption bands are measured. In addition, there are **multiple scattering processes at the leaf (mesophyll), plant, as well as at canopy level**, which determine the shape of the absorption bands.
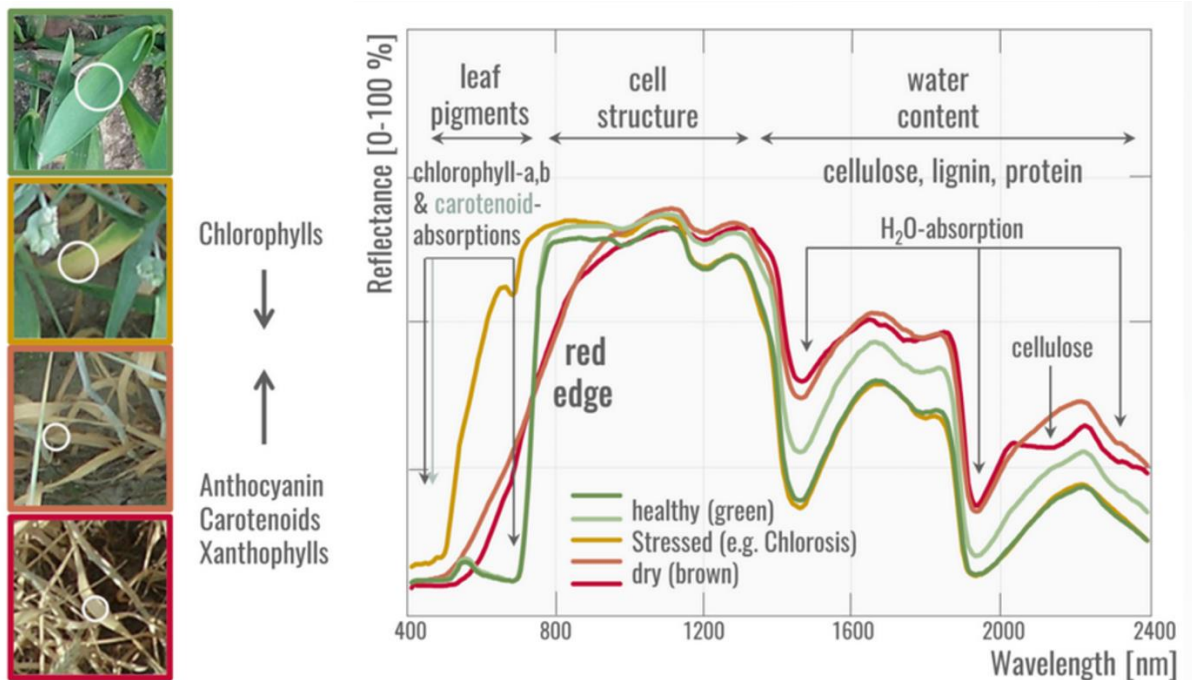
Figure 7 **Reflectance spectra from green, stressed and dying vegetation.**
Brosinsky et al. (2019) Principles of imaging spectroscopy (HYPEREdu slide collection)

In general, the **spectral reflectance curve of healthy green vegetation has a minimum in the visible (VIS)** part of the electromagnetic spectrum due to leaf pigments. Chlorophyll pigments selectively absorb blue (400–500 nm) and red (600–700 nm) light for photosynthesis and less green light (500–600 nm), resulting in a "green peak" and the green appearance of healthy vegetation to the human eye. Other pigments like carotenoids and xanthophylls have strong absorptions in the blue wavelengths range (400–500 nm) and are responsible for various leaf colors.

The **spectral reflectance curve increases greatly towards the near-infrared range (NIR)**. In the NIR (700-1300 nm), leaf absorption by pigments and other constituents is small and most energy is transmitted or reflected, depending on leaf structural characteristics, resulting in a high plateau.

The range between red (VIS) light and near infrared is characterized by a steep slope, called the "red edge" and is used to detect plant stress. The reflectance of stressed vegetation is generally higher in the VIS and lower in the infrared range as compared to healthy vegetation. There is a flattening and shift to shorter wavelengths in the red edge portion of the spectrum.

The **SWIR region (1300–2500 nm) is dominated by water absorption**. An increase in leaf moisture content results in a general decrease in reflectance, especially in the

NIR and SWIR, accompanied by an increase (depth, width) of the water absorption features near 1400 and 1900 nm.

If vegetation is stressed, e.g., drought or extreme heat, the plants reaction may not be immediately apparent to the human eye – but it is visible to an (imaging) spectrometer! Very generally, the "red edge" shifts towards shorter wavelengths and becomes flatter, and the depths of water absorption features decreases.

Finally, not only does the biochemical composition (e.g., chlorophyll content) but also the biophysical manifestation (e.g., the leaf area index) of vegetation influences the spectral signal. Vegetation is a geometrically complex phenomenon, where **the geometric layout strongly influences the way that light interacts with biophysical and biochemical constituents in the leaves**. The angular arrangement between illumination source, illuminated target and receiving sensor strongly influences the brightness of the signal, which becomes most obvious in the NIR plateau of a vegetation spectrum. Shortly after emergence, young plants tend to show steep leaf angles (erectophile). Throughout their life cycle plants will increasingly lower the leaves, especially during senescence (planophile).

By the way, **dry vegetation** – a wheat field ready for harvest for example – looks surprisingly different from green vegetation. The spectrum of dry vegetation spectrum resembles the spectrum of bare soil rather than the spectrum of green vegetation. In order to differentiate between dry vegetation and bare soil, hyperspectral information is crucial, as these two land cover types can only be distinguished using the cellulose absorption feature around 2100 nm.
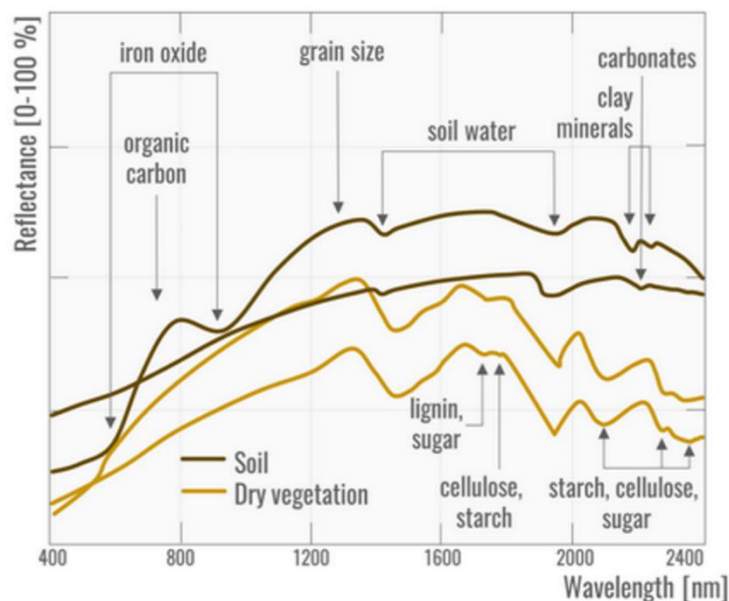
Figure 8 **Reflectance spectra of soil and dry vegetation.**
Brosinsky et al. (2019): Princiles of imaging spectroscopy (HYPERedu slide collection)

Interactive Graphs

You need to be enrolled and logged in under EO College in order to be forwarded to the interactive Graphs. Figures of those are, however, incorporated in this offline version. For the best learning experience, we recommend to check out the graphs online.

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

Interactive graph on the reflectance properties of vegetation
Available under this LINK.

The spectral reflectance properties of vegetation
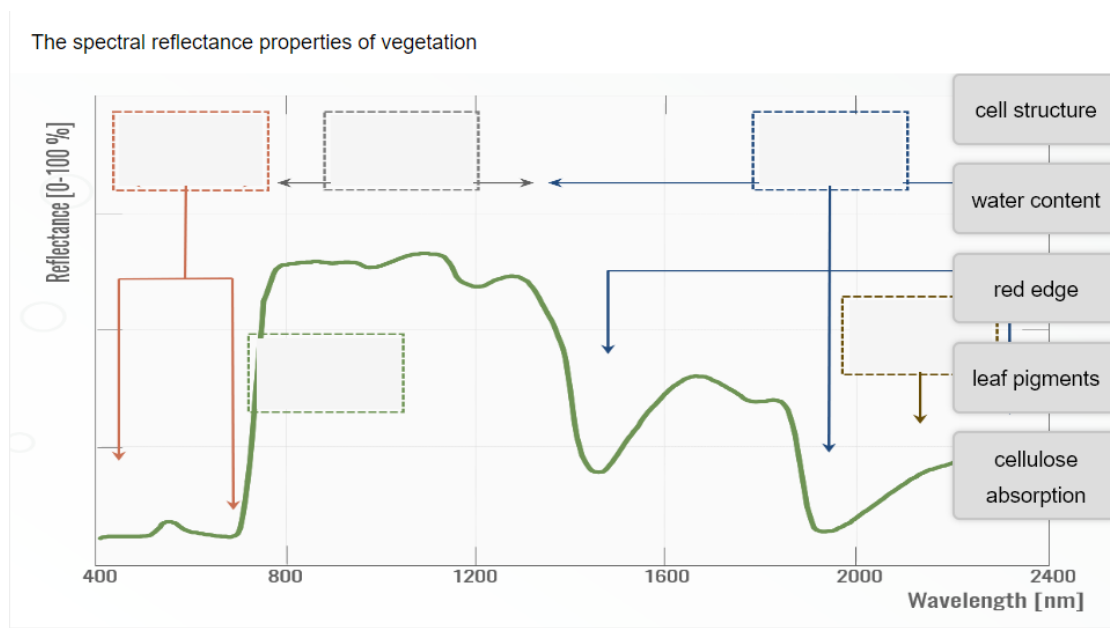
The interactive graphic below nicely displays how vegetation reflectance is high in the NIR. What the graph doesn't show, however, is that vegetation is also partially transparent in spectral regions where the reflectance is high, i.e. in the NIR. When interpreting spectral data from vegetated surfaces, we thus have to consider that the spectral signature of the underlying soil will be shining through to some extent. This effect will be less pronounced if several layers of leaves are stacked (= high LAI), but nonetheless, knowledge about the spectral characteristics of the underlying soil is very important when analyzing vegetation spectra! The spectrum of the soil is mainly influenced by its physical (e.g. grain size) and chemical (e.g. carbon content) composition, but also depends on the weather at the time of the spectral acquisition. For instance, surface soil moisture strongly influences the brightness of the soil spectral signal, but may rapidly change in space and time.

Interactive graph on the reflectance properties of vegetation
Available under this LINK.

Chlorophyll A + B (Cab) [12.5 µg/cm^2]
Leaf Water Content (Cw) [0.021 cm]
Leaf Area Index (LAI) [2.670 m^2/m^2]
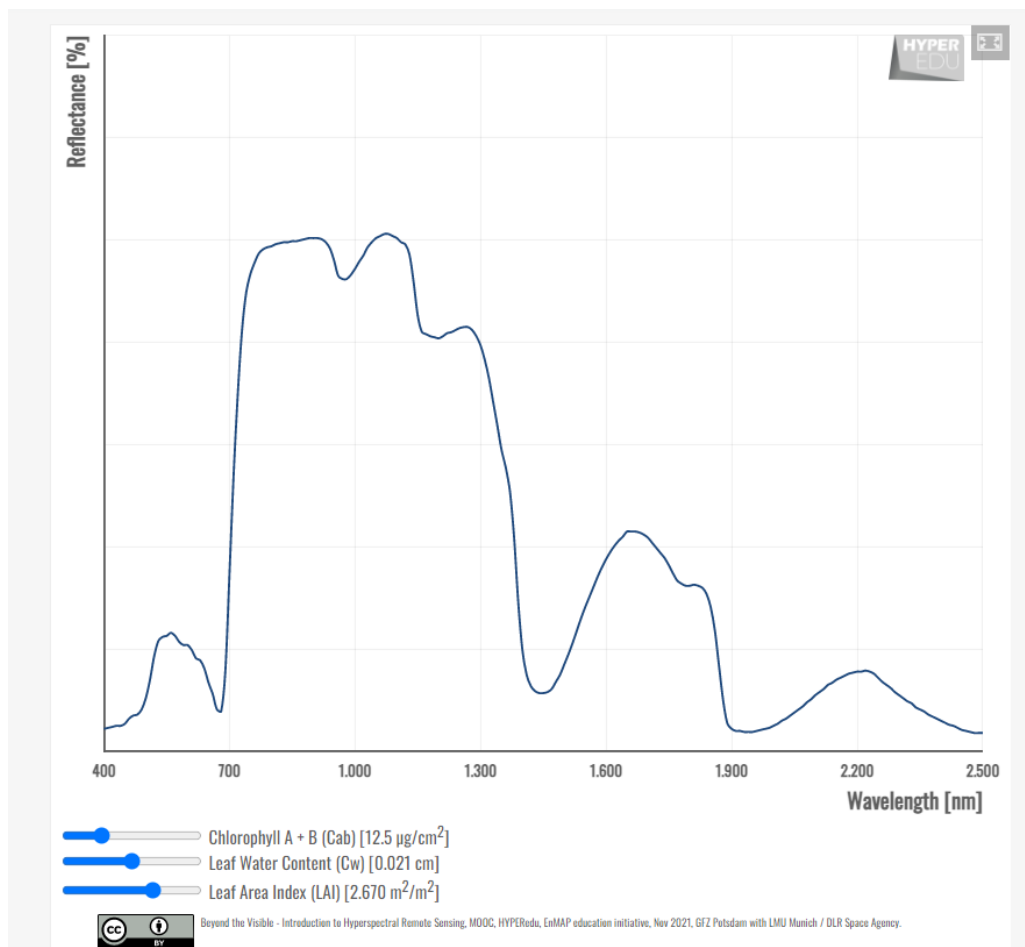
Quiz: Imaging spectroscopy of vegetation (for agricultural applications)

Fill in the blanks

Potential answers to fill in the blanks:

- red/ green/ blue

- 550 nm/ 800 nm/ 2200 nm

- cellulose/ chlorophylls/ anthocyanins

The "☐ peak" is located around ☐ nm and caused by the absorption of ☐ .

With decreasing LAI, the spectrum of green vegetation … (multiple-choice)

☐   … becomes increasingly flat (less pronounced absorption features)

☐   … remains the same except for changes in the VIS region

☐   … becomes increasingly more similar to a soil spectrum

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

☐   … the cellulose absorption feature around 2200 nm

☐   … remains the same except for changes in the VIS region

☐   … the cellulose absorption feature between 700 and 1300 nm

☐   … their water content

Assign the correct surface material to its respective spectral signature
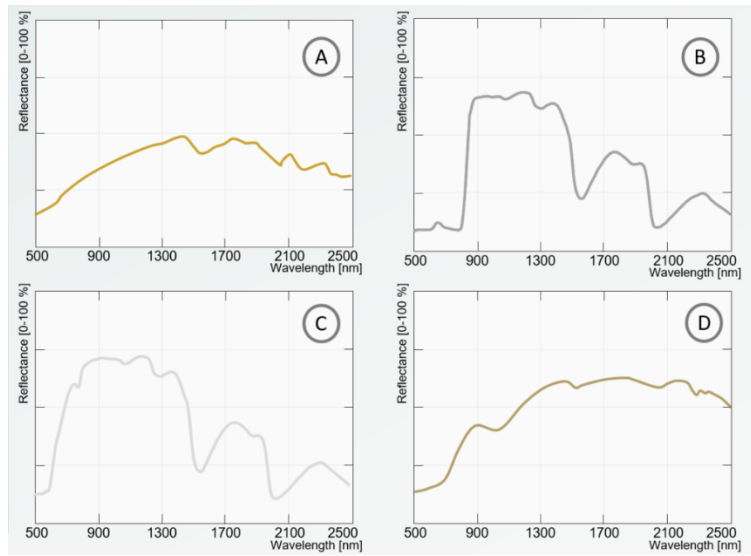
A   Choose an element

B   Choose an element

C   Choose an element

D   Choose an element

3.2 Biophysical and biochemical variables

In this topic we will provide an overview of the most relevant agricultural traits that can be predicted using remote sensing data with examples of (spaceborne) hyperspectral mapping. **Information of interest consists of functional traits, variables or features of agricultural systems**, and how these vary in space and time (Weiss et al., 2020). The nature of these agronomic traits can be:

- typological (e.g. crop type),
- biophysical (e.g. soil moisture),
- morphological (e.g. foliage height diversity, leaf dry mass per leaf area)
- biochemical (e.g. leaf nitrogen content),
- biological (e.g. crop phenology),
- structural-geometrical (e.g. leaf inclination, LAI).

Variables vs. Parameters

Note that the term "variable" is something that is measurable and has a physical or agronomical meaning (Jeuffroy et al., 2014). In contrast, a parameter is something resulting from an empirical fitting or model. Hence, we prefer the term variable in this context.

We distinguish between **primary variables** and **secondary variables**. Primary variables, are directly involved in radiative transfer mechanisms. Some variables of interest, such as crop productivity, irrigation needs or phenology, however, result from a series of intertwined biophysical processes within the soil-plant-atmosphere continuum. These variables are so-called secondary variables and are not directly related to the radiative transfer mechanisms and thus cannot be derived directly from imaging spectroscopy data (they can nevertheless be accessed from remote sensing data in combination with process modelling using data assimilation strategies, Weiss et al., 2020). **In this course, we will focus on primary variables**.
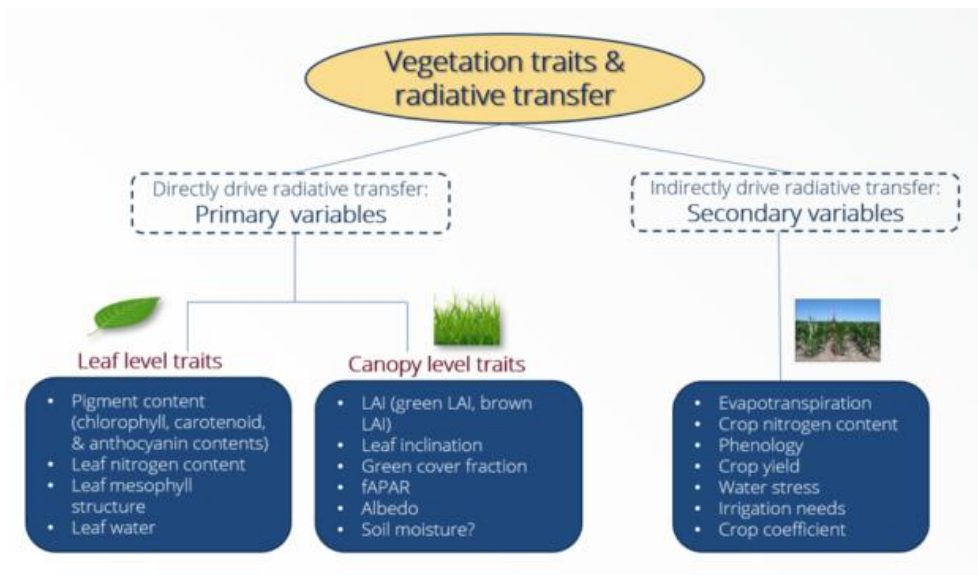
Figure 9 **Primary and secondary variables in imaging spectroscopy.**

Primary variables – Leaf traits

Leaf level traits **describe the biochemical and morphological properties of leaves**, including pigments (chlorophyll a + b, carotenoids, anthocyanins), nitrogen, phosphorus, leaf mass per area, leaf water content, carbon and nonstructural carbohydrates (sugars, starches). **These traits are mainly involved in photosynthetic processes and carbon uptake. Leaf structural compounds** include cellulose, fiber, lignin and hemicellulose. Typically, leaf traits are given in area-based (µg / cm^2) or mass-based units (% or mg/g).

Leaf chlorophyll content (LCC)

Figure 10 **Exemplary map of LCC, generated using the hybrid processor of the EnMAP-Box Agri-tools: Neural network trained over PROSAIL data base (agricultural region of Neusling (Bavaria, Germany)**.
In courtesy of Martin Danner, Hybrid Inversion tool, Agri-Apps (EnMAP-Box)

Chlorophyll molecules allow the conversion of absorbed solar irradiance into stored chemical energy.

This is accomplished by harvesting light energy and supplying electrons to the electron transport chain, leading to the production of NADPH for the reactions of the Calvin–Benson Cycle (Croft and Chen 2017).

The amount of solar radiation absorbed by a leaf is largely a function of the foliar concentration of photosynthetic pigments. Therefore, low leaf chlorophyll content (LCC) limits the photosynthetic capacity and reduces primary productivity of crops (plants).

LCC is usually quantified in units of µg chlorophyll per cm^2 (leaf area), or $\mu mol\, m^{-2}$ or µg g^{-1}. *In situ* measurements of LCC are usually performed non-destructively via the Konica Minolta device Chlorophyll Meter SPAD-502Plus.

"In agricultural systems, the accurate spatial mapping of leaf chlorophyll content is important for monitoring vegetation health and plant stress, which can be used to guide fertilizer application in order to optimise crop yield and reduce excessive nutrient loss." *(Croft & Chen 2017)*

Leaf carotenoid content (C_{xc})

Plants contain a number of different types of carotenoids (C_{xc}), which fall into the subgroups of carotenes or xanthophylls. The most common carotenoid pigments present in leaves are represented b-carotene and five xanthophylls (lutein, zeaxanthin, violaxanthin, antheraxanthin, and neoxanthin) (Croft & Chen., 2017).

Carotenoids and xanthophylls play an important role in photoprotection, accessory light harvesting and energy transfer (Gitelson et al. 2002; Kong et al. 2017). They are present in variable proportions during the differentiation

Figure 11 **Exemplary map of Leaf carotenoid content (C_{xc}), generated using Analyze Spectral Integral (ASI) of the EnMAP-Box Agri-tools (Barrax, Spain)**. Figure reprinted from Wocher et. al. (2020)

and ageing of leaves, but abiotic stresses can inhibit carotenoid production (Hank et al., 2019). The amount of carotenoids is commonly expressed in different units, e.g., as mass per unit surface area ($\mu g\ cm^{-2}$), or as mass per unit fresh leaf weight ($mg\ g^{-1}$).

"Carotenoid pigments provide fruits and flowers with distinctive red, orange and yellow colors as well as a number of aromas, which make them commercially important in agriculture, food, health and the cosmetic industries." (Cuttriss et al., 2011)

Leaf anthocyanin content (C_{ant})

Anthocyanins (C_{ant})are the most common class of flavonoids, i.e. **the most widespread red pigments** (Hank et al., 2019). They are responsible for the orange to red, or purple to blue coloration in plant tissue depending on the molecule, temperature, and pH value. Flavonoids are commonly found in blueberry, raspberry, black rice or black soybean (Tanaka et al. 2008).

Figure 12 **Exemplary macro shot of a wild berry.**

"Anthocyanins are actively produced as a result of environmental stresses (e.g., low or high temperatures), during senescence and following budburst, before the photosystems are fully developed." (Gamon & Surfus, 1999; Croft & Chen, 2017).

Hence, they can be of interest for precision agriculture, since anthocyanins are typically present when plants suffer from

environmental stresses such as drought, freezing, air pollution or nutrient deficiency (Lee & Gould 2002; Springob et al. 2003).

Leaf water content (C$_W$ or EWT)

Leaf water content (C$_w$) or equivalent water thickness (EWT) describes the thickness of a theoretical layer of water (in cm), which absorbs radiation according to the Lambert–Beer law (Nobel, 2009). Hence, EWT corresponds to the volume of water that is stored within the cells of living vegetation (Hank et al., 2019). From a remote sensing perspective, it is difficult to decouple the contributions of leaf water content from LAI. Thus, the total canopy water content per unit ground area (CWC, g m^{-2}), rather than leaf EWT is usually "observed" or retrieved (Clevers et al., 2010).
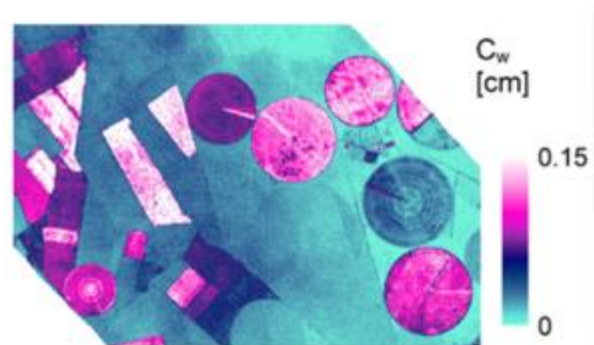
Figure 13 **Exemplary map of Leaf water content (EWT, Cw), generated using Analyze Spectral Integral (ASI) of the EnMAP-Box Agri-tools (Barrax, Spain)**. Figure reprinted from Wocher et. al. (2020)

"One aspect of detecting stress in plants from hyperspectral data that has received considerable attention is the measurement of leaf water content." (Murphy et al. 2019). As it is difficult to assess leaf water content remotely, the total canopy water content per unit ground area (CWC) is retrieved as a measure for the moisture state of a canopy, which is of interest for practical farming for the detection of plant water stress.

Leaf mass per area (LMA)

Leaf Mass per Area (LMA) denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m² or g per cm² leaf area. It is a measure of the leaf composition: the first leaves developed by a plant at the beginning of its growth cycle are usually lightweight, so that the area available for interception with solar radiation expands rapidly during early growth phases. During later development stages, plants tend to invest more energy into the structural stability of the leaves, causing the LMA to

increase over the growing period (Hank et al., 2019). LMA is a fundamental leaf functional trait playing a key role in ecosystem modelling (Asner et al. 2011).

"LMA is an essential indicator of plant functioning, including photosynthetic and respiratory rates, chemical composition or resistance to herbivory (de la Riva et al. 2016). The importance of LMA for farming compared to the other variables is therefore rather indirect but nonetheless important, in particular regarding the relationship of LMA to photosynthesis–nitrogen relationships (Poorter & Evans 1998)." Hank et al. (2019)
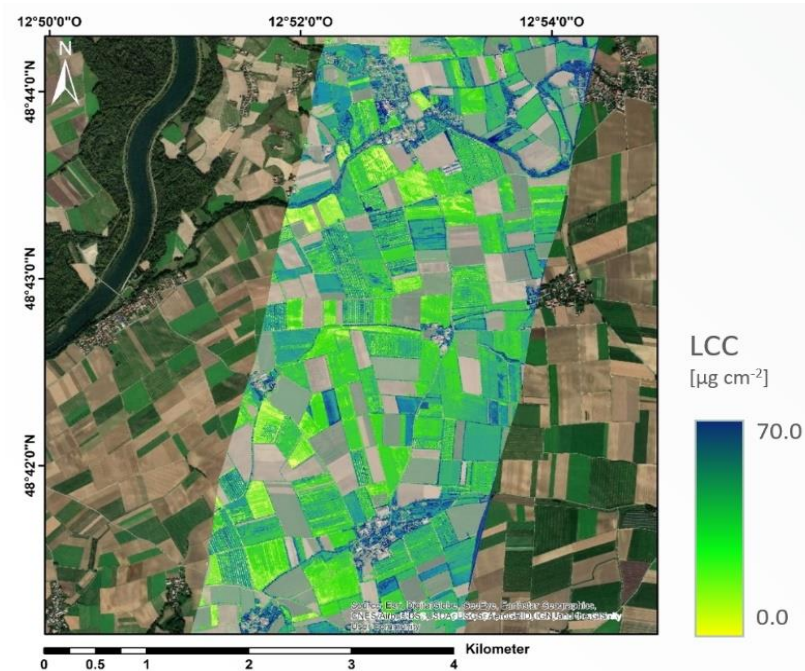

Figure 14 **Exemplary map of LMA, generated using the hybrid processor of the EnMAP-Box Agri-tools: neural network trained over PROSAIL data base (Neusling, Bavaria, Germany)**.
In courtesy of Martin Danner, Hybrid tool, Agri-Apps (EnMAP-Box)

Leaf protein (Cp) / nitrogen content (N)

N is taken up by the roots from soil in the form of NH_4^+ and NO_3^-, and it is a rather small component of leaf dry weight, ranging from 0.3% to 6.4% (Wright et al., 2004). A large amount of N is invested in proteins (and chlorophylls) within the leaf cells. Proteins are the major N containing biochemical constituent of plants (Kokaly et al., 2009).
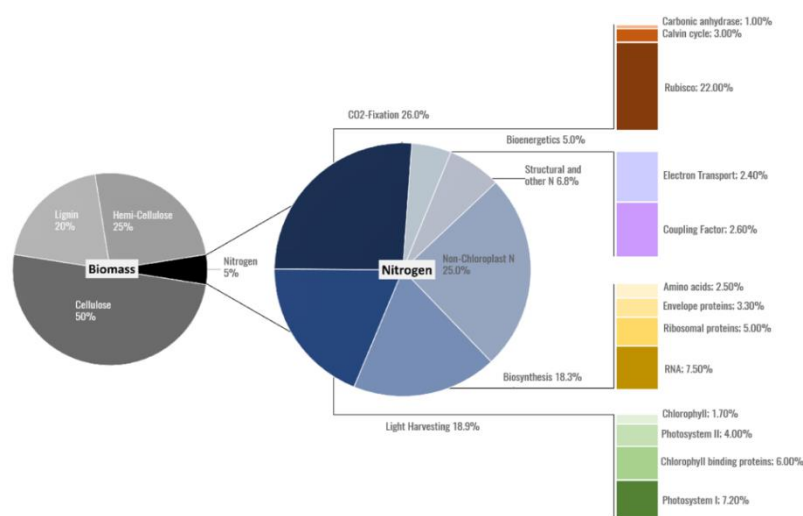
Figure 15 **Nitrogen as key component of biomass (left) and its proportional allocation in a C3 plant leaf (right). Adapted from Chapin et al. (1987).**
Figure reprinted from Berger et al. (2020)

Vegetation growth is not a static but a dynamic process of constant nitrogen turnover (Kattge, 2002). Early in a growing season N is bound in vegetative tissues. During the reproductive phase, N is moved or reallocated from the vegetative organs (leaves) to reproductive structures, such as seeds, ears or fruits (Ohyama, 2010, see also review study Berger et al., 2020a). For agriculture, it is usually not the leaf protein content that is important, but the protein content in the harvested crop, i.e. in the grain. However, since electromagnetic radiation cannot penetrate the grain, crop nitrogen content cannot be measured with remote sensing. For this purpose, growth models must be used that reproduce nitrogen transformation and translocation in the crop. Therefore, while we count **leaf** nitrogen content as "primary variable", **crop** nitrogen content is ranked as "secondary variable".

„Nitrogen availability produces rapid and early crops' growth, increases protein content of crops, facilitates the uptake and utilization of other nutrients as potassium and phosphorous, improves fruit quality, and controls overall growth of plants [..] Analyzing the N amount in soil and crops and the application of N fertilizer in the event of a deficit are essential to improve crop production…" (Salima et al., 2019)

Carbon-based leaf constituents (CBC)

Carbon-based constituents (CBC) include cellulose, lignin, hemicellulose, sugars and starch. These abundant molecules produced by terrestrial photosynthesis are the main components of non-photosynthetic vegetation (NPV). Each constituent of CBC has a specific carbon content (Ma et al., 2018). "Together with the carbohydrate polymers cellulose and hemicellulose, lignin forms the largest portion of "lignocellulosic" plant materials. Thus, lignin accounts for a substantial portion of the total organic carbon in the biosphere, surpassed only by cellulose." (Frei et al., 2013)

"Lignin from crop residues plays an important role in the soil organic carbon cycling, as it constitutes a recalcitrant carbon pool affecting nutrient mineralization and carbon sequestration. Its function in plants also includes the defence against abiotic and biotic stresses, especially pathogens and insects" (Frei et al., 2013).

Sun-induced fluorescence (SIF)

During photosynthesis, plants absorb sunlight in the 400–700 nm spectral range. A small fraction of the absorbed energy is re-emitted at longer wavelengths (650-800 nm) as a faint signal known as sun-induced chlorophyll fluorescence (SIF). However, the very coarse spatial resolutions of current satellite SIF sensors (40 km GOME-2), and also those in the near future, e.g. FLEX with 300 m, is limited for agricultural applications, except at regional/global scales.
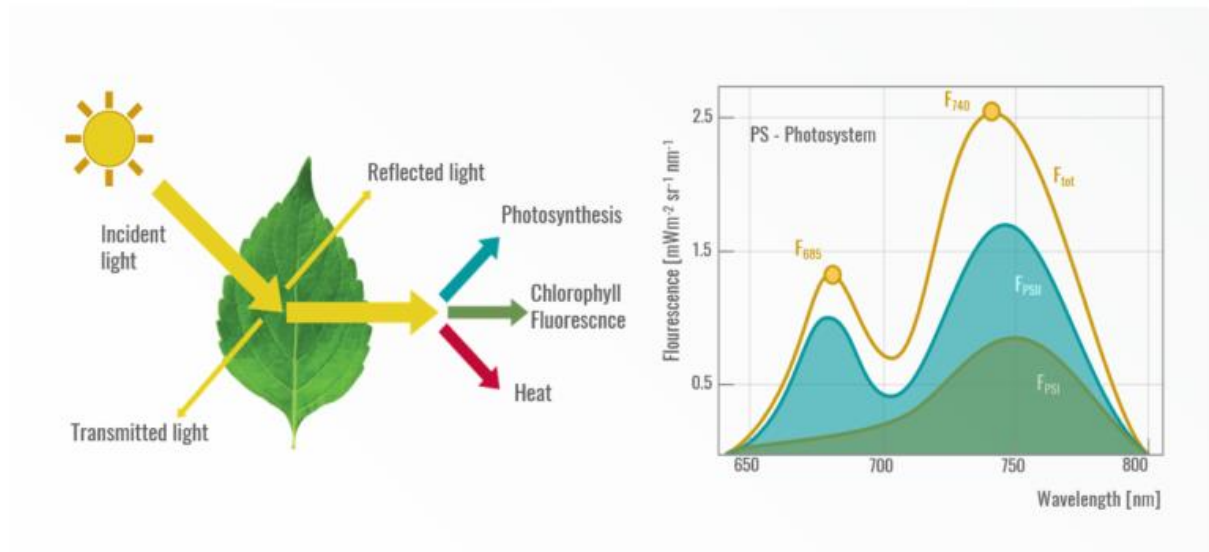
Figure 16 **The process of sun-induced fluorescence (SIF).**
Images reprinted from Sang-O, J. (2017) and Couleur (2018)

The strong link between SIF and photosynthesis opens possibilities of inferring gross primary productivity (GPP) (=gross uptake of atmospheric carbon dioxide (CO2)) from SIF (Schlau-Cohen & Berry, 2015; Mohammed et al., 2019).

Summary of leaf level traits

- The inference of leaf level traits from remote sensing observations is **challenging** as the strength of the signal transmitted from leaf to canopy level is controlled by structural variables of the canopy, such as LAI or leaf angle distribution (Xie et al., 2019).

- Note that there are also **stems and other plant organs** (fruits, flowers, heads …), which often are not considered in modeling approaches!

- The majority of methods estimating leaf level traits rely on parametric regressions, and some machine learning approaches (more information on retrieval approaches in the next lesson).

Primary variables – Canopy level traits

Canopy level variables or traits mainly describe the **structural properties of a vegetation stand**. In contrast to leaf biochemicals and leaf structural compounds, the added value of hyperspectral data in comparison to multi-spectral data for the retrieval of canopy level traits is less obvious. Nonetheless, these traits are of essential importance for agriculture due to their strong link to crop status and yield potential (Atzberger, 2013).

The dimensionless leaf area index (LAI) characterizes plant canopies and is defined as green leaf area [m^2] per unit ground area [m^2]. It is of upmost importance for eco-physiology in many ways: in modelling, it serves as a scaling factor, by controlling processes like photosynthesis and evapotranspiration (Weiss et al.,2004; Bréda, 2003). Acting as a transition zone between plants and the atmosphere, most

Figure 17 **Schematic representation of leaf area index (LAI) concept.**
HYPEREdu (2022)

processes of gas and water exchange as well as the interception of rain water, take place on the surface of leaves (Bréda, 2003). By extinction of incident radiation, variations in the LAI influence the micro climate within and above the canopy (Welles, 1990). Combining the leaf area parameter with information on the distribution of leaf angle, it is possible to model the amount of absorbed photosynthetically active radiation (APAR). Ground-based measurements of LAI play a crucial role for the calibration and validation of remote sensing data.

The biophysical trait of LAI has attracted a lot of interest in optical remote sensing studies related to agriculture. "Many applications, including crop growth and yield monitoring, require accurate long-term time series of leaf area index (LAI) at high spatiotemporal resolution with a quantification of the associated uncertainties" (Yin et al., 2019)
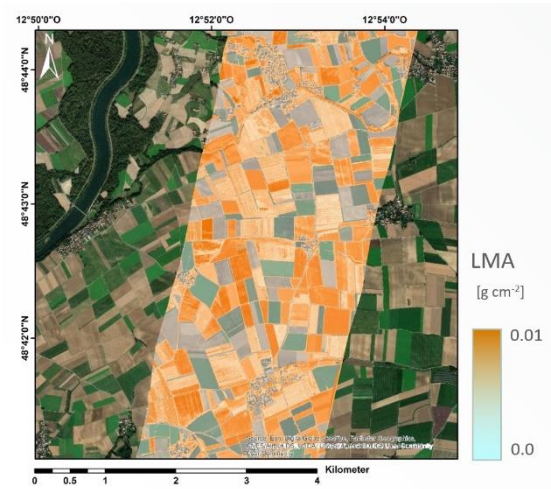
Leaf inclination angle distribution (LAD)

Figure 18 **Exemplary map of ALIA, generated using the hybrid processor of the EnMAP-Box Agri-tools: Neural network trained over PROSAIL data base (agricultural region of Neusling (Bavaria, Germany)**.
In courtesy of Martin Danner, Hybrid Inversion tool, Agri-Apps (EnMAP-Box)

Leaf inclination angle distribution (LAD) or average leaf inclination angle (ALIA) is an important characteristic of vegetation canopy structure affecting light interception within the canopy. Leaf orientation with respect to the position of the sun is a key factor in determining the amount of light intercepted by a leaf, and also affects the fraction of incident sunlight that penetrates the canopy to lower layers of leaves (Huemmrich 2013). The orientation of a leaf is described by its azimuth and inclination angles (in °).

Information of ALIA can be also used as an indicator of water-stress: significant correlations were found between inclination angle and leaf water content in leaflets and petioles of crops (Nagasuga et al., 2013).

Fractional vegetation cover (fCOVER or FVC)

Green fractional vegetation cover is an important biophysical variable describing the Earth's surface system. It "is generally defined as the ratio of the vertical projection area of above-ground vegetation organs on the ground to the total vegetation area", Liang & Wang (2020). The fraction of the green vegetation in the nadir direction (in %), is used to separate vegetation and soil in energy balance processes, including temperature and evapotranspiration (Li et al., 2015).
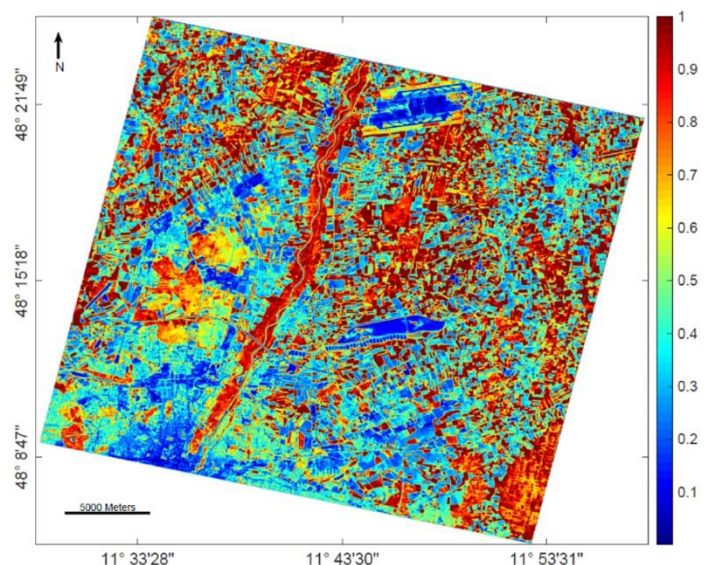
Figure 19 **Exemplary map of fCOVER estimations (left), based on a hybrid retrieval model using ARTMO MLRA-toolbox: GPR trained over SCOPE model simulated data base (Munich, Germany)**.
In courtesy of Jochem Verrelst, ARTMO

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Fractional vegetation cover is also known as **green ground cover** (GGC in %) (Zillmann et al., 2015).

Fractional vegetation cover is useful for various applications in the field of agriculture, ranging from irrigation (e.g., Calera et al., 2001) and crop residues management (e.g., Daughtry et al., 2005) to yield estimations (e.g. Castaldi et al., 2015).

Fraction of absorbed photosynthetically active radiation (fAPAR)

Photosynthetically active radiation (PAR) corresponds to the incoming solar radiation in the spectral range of 400–700 nm while absorbed photosynthetically active radiation (APAR) corresponds to the amount of PAR absorbed by the plant for photosynthesis (Gallo and Daughtry 1986). The fraction of absorbed photosynthetically active radiation (fAPAR) is the proportion of PAR absorbed by the plant, expressed as fraction. fAPAR is an important biophysical variable in models assessing

Figure 20 **Exemplary map of fAPAR estimations (left), based on a hybrid retrieval model using ARTMO MLRA-toolbox: GPR trained over SCOPE model simulated data base (Munich, Germany).**
In courtesy of Jochem Verrelst, ARTMO

the primary productivity of vegetation and, more generally, in carbon cycle models between the terrestrial boundary layer and the atmosphere (Vina and Gitelson 2005, Rahmann et al., 2014). According to Cawse-Nicholson et al. (2021), fAPAR is **not strictly a trait**, though it was listed alongside others due to its direct relation to primary productivity (Zhang et al., 2012).

Remote sensing time-series of fraction of absorbed photosynthetically active radiation (fAPAR) have been "confirmed to be a reliable tool for regional crop yield forecasting with a strong potential to contribute effectively to operational systems such as those currently running at continental/global level (GIEWS, NASS, FAS, CropWatch or MCYFS)." (López-Lozano et al., 2015)

Canopy nitrogen content mapping

Nitrogen (N) is a rather small component of leaf dry weight (see leaf protein (Cp) / nitrogen content (N) in leaf level traits). However, it controls the overall growth of plants and "the application of N fertilizer in the event of a deficit are essential to improve crop production ..." (Salima et al., 2019), which is why analyzing its amount in soil and plants is of specific interest at canopy scale.

„Nitrogen availability produces rapid and early crops' growth, increases protein content of crops, facilitates the uptake and utilization of other nutrients as potassium and phosphorous, improves fruit quality, and controls overall growth of plants [..] Analyzing the N amount in soil and crops and the application of N fertilizer in the event of a deficit are essential to improve crop production..." (Salima et al., 2019)
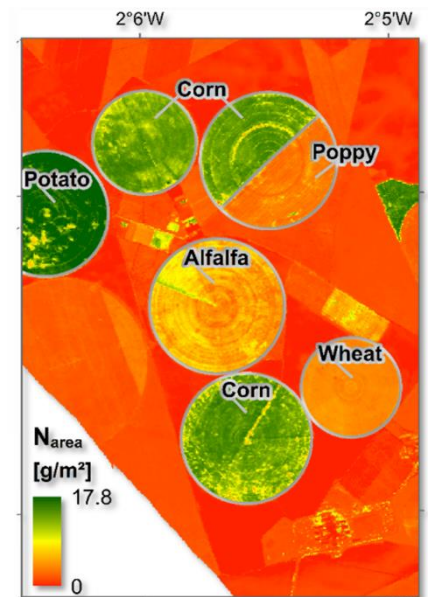
Figure 21 **Aboveground N content generated by heteroscedastic Gaussian process regression (VHGPR) modelling (Barrax, Spain).** Adapted from Berger et al. 2020b

Non-photosynthetic vegetation (NPV)
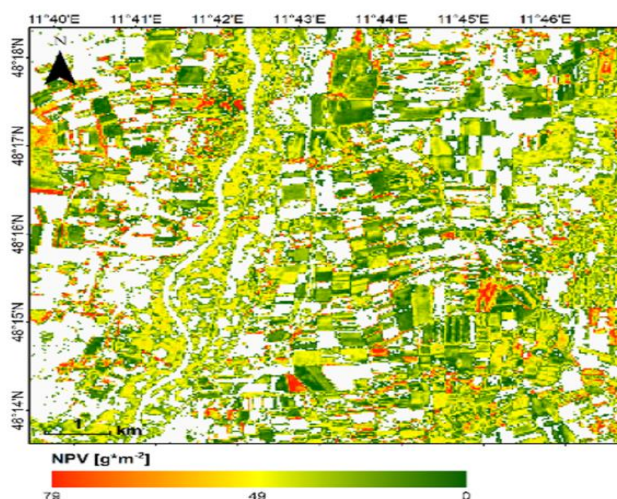
Figure 22 **Exemplary map of NPV biomass, based on hybrid retrieval method using ARTMO MLRA-toolbox: GPR trained over PROSAIL-PRO simulated data base**. PRISMA scene over North of Munich, Bavaria, including Munich-North-Isar test site

NPV refers to plant parts that do not perform photosynthesis, such as plant litter, crop residues, senescing foliage, branches and stems (Li & Guo 201, Hank et al., 2019). Crop residue (CR) on the soil surface or a protective mulch significantly reduces erosion (by wind and water), nutrient loss, evaporation, and soil temperature. Further, it reduces soil compaction due to agricultural machinery (Pepe et al., 2020) and enhances soil organic carbon through improved soil structure.

In addition, crop residues may contain significant amounts of nitrogen, which enter the soil through ploughing.

For agricultural applications, NPV biomass (e.g. in g m^{-2}) or crop residue cover (%) is particularly interesting since it indicates (seasonal) drought events or other severe injuries.

From leaf to canopy level traits

- The majority of methods estimating canopy level traits rely on machine learning approaches (more information on retrieval approaches and widely used models such as PROSAIL in the next lesson – Lesson 4).

- Typically, LAI is used to upscale leaf-level variables to the canopy level (e.g. LCC to canopy chlorophyll content). Global sensitivity analysis (GSA) of the PROSAIL model (Verrelst et al., 2015) showed that LAI is the primary driving variable of canopy reflectance, explaining up to 40% of the total variability (with interactions). Another important variable with similarly high impact is leaf inclination angle distribution (LAD).

- The SAIL model (Verhoef, 1984), and its adapted and improved versions, is a commonly used radiative transfer model to describe radiation interaction with the canopy for agricultural crops, usually it is coupled with the PROSPECT model to "PROSAIL".

- A specific extension of PROSAIL is the SCOPE model family (van der Tol et al., 2009), coupling radiative transfer, energy balance, and photosynthesis models. A very recent adaption is provided by Pacheco-Labrador et al. (2021), namely the senSCOPE model for canopies combining green and brown senesced leaves.

- For a better representation of row crops and corresponding derivation of biophysical / biochemical variables, more complex 3D or hybrid models should be used, such as DART (Gastellu-Etchegorry et al., 1996).

Secondary variables

One example of secondary variables is the **phenological state** of the canopy: The spectral signature alone does discriminate the fine increments of phenological progress that in practical agriculture normally are monitored using the BBCH scale on phenology. Only, when a-priori knowledge (e.g. crop type and crop variety) is available and additional information (e.g. meteorological data) is considered, are we able to delineate the growth stage with adequate accuracy. Another important secondary variable is **biomass**, as the accumulation of biomass in agriculture determines the spatial distribution of plant protection agents. Electromagnetic radiation in the optical domain does not penetrate the lignified parts of the canopy. Measuring biomass from remote sensing alone therefore remains difficult. Only when canopy level variables derived from remote sensing (e.g. LAI) are combined with meteorological data, soil maps, terrain information etc. with the help of growth process models, can we gain access to this crucial management variable.

Quiz: Biophysical and biochemical variables

With respect to vegetation traits, what are "primary variables"? (multiple-choice)

☐   Variables that are most important for agricultural 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 is the difference between leaf and canopy traits? (single-choice)

☐   Leaf level traits can only be assessed in the laboratory while canopy level traits can be assessed in the field

☐   Leaf level traits describe the biochemical and morphological properties of leaves while canopy level traits mainly describe the structural properties of a vegetation stand

☐   In fact, there is not really a difference

Which of the traits below are described as canopy traits? (multiple-choice)

☐   Chlorophyll

☐   Leaf Area Index

☐   Leaf Water Content

☐   Fractional vegetation cover (fCOVER or FVC)

☐   Leaf inclination angle distribution

What definition corresponds to the LAI? (single-choice)

☐   The LAI characterizes plant canopies and is defined as green leaf area [m^2] per unit ground area [m^2]

☐   The LAI denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m^2 or g per cm^2 leaf area

☐   The LAI, also called average leaf inclination angle (ALIA), is an important characteristic of vegetation canopy structure affecting light interception within the canopy

3.3 Ground reference data acquisitions

Campain/ 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 agricultural applications will be presented in the following video.

In the course you will see several **videos that we have made interactive for you**. They contain questions that you can try to answer. The answers are not graded, you have countless attempts, you can skip them, and even rewind and fast-forward through the video to find the correct answer. **Give it a try!** They will help you prepare for the graded quizzes and to take away the most important aspects of each topic.

> In this document, you will find the questions below the videos. The questions can be answered with the help of the videos. To check the answers, the video must be watched online in the MOOC on https://eo-college.org/courses/beyond-the-visible/.

Ground reference data acquisition in the field

How are ground reference data collected in the field? Come and join us (again?) to the LMU test sites near Munich (if you've taken the basic MOOC 'Beyond the Visible: Introduction to Hyperspectral Remote Sensing' the first minute might seem familiar).

Video: Agri-03: Imaging Spectroscopy for Agricultural Application - Field Data Acquisition

Video URL: https://youtu.be/e7FkCjzZNZM

VIDEO: Field Data Acquisition

What would be unuseful ancillary information? (single choice)
☐ weather conditions (sampling day or previous days)
☐ time of day
☐ weather forecast

You might have noticed that we measure some variables in the field that we did not yet define. For example, we measured crop height as it is an important variable for modelling the growth of biomass. It determines how rough the surface is in relation to advective air currents and thus how far the wind can penetrate the stand to promote gas exchange. Other variables cannot be measured in-situ (in the field) but need to be assessed in the lab. Our student assistants will show you how we assess Leaf Mass Area (LMA) and aboveground biomass.

Video: Agri-04: Imaging Spectroscopy for Agricultural Applications - Lab Data Acquisition

Video URL: https://youtu.be/C7jmsZnWgHE

VIDEO: Lab Data Acquisition

Which variable(s) can be analysed from the dried leaf samples in addition?
(single choice)

☐ The dry samples are ground into fine powder using a laboratory mill. This powder is then analyzed for percentage carbon and nitrogen content via combustion in a special analyzer.

☐ The dry samples are used to estimate the biomass content of the respective sampling site.

☐ The dry samples are used to assess plant water content

Other variables that cannot be assessed in the field with high reliability are anthocyanins and carotenoids, they, too, need lab work. However, their amounts are closely correlated to chlorophyll content during the phase of vegetative growth, a relationship that we exploit in our models as you will see later in the "hands-on" exercises.

Besides, we did not assess fCover and fAPAR. For those measurements, we refer you to Muir et al. (2011) and Li et al. (2021), respectively. Actually, in order to show you how we take reference measurement with our field spectroradiometer we've taken you to the LMU test sites near Munich in the basic MOOC too. If you haven't seen the video yet, you can do so here:

Video: Basic-12: Sensor technologies & data acquisition techniques: ASD Field

Video URL: https://youtu.be/7S1XoN-NifM

Quiz: Ground reference data acquisitions

Which of the Variables below can only be measured in the lab? (multiple-choice)

☐   Chlorophyll

☐   Leaf Mass Area (LMA)

☐   Leaf Area Index (LAI)

☐   Leaf Carbon and Nitrogen contents

☐   Plant Water Content

☐   Phenology

What does the SPAD chlorophyll meter measure to assess chlorophyll content? (single-choice)

☐   diffuse radiation, i.e. transmission, underneath the canopy in combination with measurements above the canopy to serve as reference

☐   absorbance of LED-light by the leaf at two different wavelengths in the spectral domain of red and near-infrared

☐   Chlorophyll is linked to plant phenology and can be assessed with the BBCH scale

☐   absorbance of LED-light by the leaf at two different wavelengths in the spectral domain of near-infrared and shortwave infrared

3.4 Resources 'Methodological aspects'

In this section, we have assembled resources used for the creation of this lesson that we recommend you use 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).

You can find most figures of this lecture in the HYPERedu slide collection, available on EO-College.

Sources for further reading

Topic 3.1: Imaging spectroscopy of vegetation (for agricultural applications)

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Topic 3.2: Imaging spectroscopy of vegetation (for agricultural applications)

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Topic 3.2: Imaging spectroscopy of vegetation (for agricultural applications)

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Quiz: Introduction to imaging spectroscopy for agricultural applications

Please sort the traits below into canopy and leaf level traits

Pigments	Choose an element
LAD	Choose an element
LMA	Choose an element
SIF	Choose an element
LAI	Choose an element
Fractional Vegetation cover (fCOVER or FVC)	Choose an element
Leaf Water Content	Choose an element
Leaf inclination angle	Choose an element
ALIA	Choose an element

Which ground reference data can be collected in the field with no need for lab analyses? (multiple-choice)

☐ Leaf chlorophyll content
☐ Leaf area index
☐ Leaf mass per area
☐ Phenology

Which of the variables below are secondary variables that cannot be inferred directly from imaging spectroscopy data? (multiple-choice)

☐   LAI

☐   Phenology

☐   Pigment content

☐   Irrigation needs

Can secondary variables be retrieved from imaging spectroscopy data? (single-choice)

☐   Yes, as they indirectly drive radiative transfer they can be modelled using imaging spectroscopy data, though sometimes additional information is helpful

☐   Yes, but only one or two as they are not connected with radiative transfer

☐   No, unfortunately not

With decreasing chlorophyll content, the spectrum of green vegetation ... (single-choice)

☐   ... becomes increasingly flat (less pronounced absorption features)

☐   ... remains the same except for changes in the VIS region

☐   ... becomes increasingly more similar to a soil spectrum

Assign where the reflectance of vegetation is influenced by …
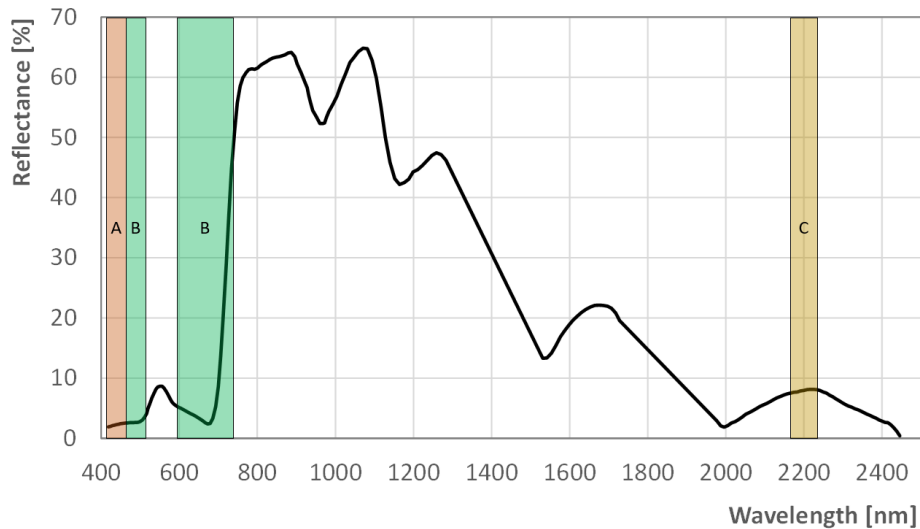
A		Choose an element
B		Choose an element
C		Choose an element

Fill in the blanks

Potential answers to fill in the blanks:

- red/ green/ blue

- 550 nm/ 800 nm/ 2200 nm

- cellulose/ chlorophylls/ anthocyanins

The "[   ] peak" is located around [   ] nm and caused by the absorption of [   ].

With respect to vegetation traits, what are "primary variables"? (multiple-choice)

☐   Variables that are most important for agricultural 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 is the difference between leaf and canopy traits? (multiple-choice)

☐   Leaf level traits can only be assessed in the laboratory while canopy level traits can be assessed in the field

☐   Leaf level traits describe the biochemical and morphological properties of leaves while canopy level traits mainly describe the structural properties of a vegetation stand

☐   While the majority of leaf level traits rely on parametric regressions, canopy level traits are often retrieved using machine learning approaches

☐   In fact, there is not really a difference

What definition corresponds to the LAI? (single-choice)

☐   The LAI characterizes plant canopies and is defined as green leaf area [m^2] per unit ground area [m^2]

☐   The LAI denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m^2 or g per cm^2 leaf area

☐   The LAI, also called average leaf inclination angle (ALIA), is an important characteristic of vegetation canopy structure affecting light interception within the canopy

4. Methodological aspects

Welcome to our second lesson! Did you ever wonder during the first lesson how to actually retrieve variables – or traits – 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 agricultural imaging spectroscopy. Then we will provide information on the state of the art methods in more detail that 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: Agri-05: Imaging Spectroscopy for Agricultural Applications - Lesson 04 Intro

Video URL: https://youtu.be/h9WkC5T1MOA
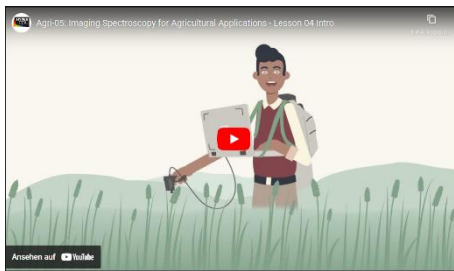
Let's move on with the first topic of this lesson!

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 an agricultural context, including some updates (YES! EnMAP data is now available!!!) 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 future launch 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 data sources for **spaceborne** imaging spectroscopy data.

EnMAP

No, it's not a joke – after years of delay (to make it a perfect sensor), EnMAP finally launched into space on April 1st 2022! Wow!

After about seven months of commissioning phase, during which data was calibrated and validated, the first data is finally becoming available to the public.

There are two main entry points to **get EnMAP data using the Data Access Portal**: the EnMAP Instrument Planning Portal and the EOWEB® GeoPortal. 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.

Prisma

PRISMA funded 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 for the previous MOOC.

In the **first video you will get a short overview of the PRISMA mission and learn step by step how to register in the PRISMA data portal**. The **second video demonstrates how to access the PRISMA data catalogue to search for archived data**. The **third video shows how to request new PRISMA acquisition in the PRISMA data portal**.

Hyperion

The first 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 discussing the available search options.

Airborne

Right, airborne data are expensive to acquire and acquisitions are rare. Nevertheless, some projects ares 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-NG is an imaging spectrometer that measures reflected radiance at 5nm 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-Next Generation 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.

EnMAP Campaign Portal
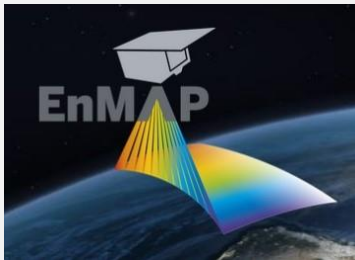
The EnMAP Campaign Portal **provides access to airborne hyperspectral image data sets along with simulated EnMAP data** that were generated using the EnMAP end-to-end simulation tool (EeteS). In addition, **associated in-situ data from field and laboratory measurements** are provided. The flight campaigns 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 set up to provide general information about all the campaigns and direct links to the datasets. The data is freely available to the scientific community under a Creative Commons License through the GFZ Data Services.

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 plugins 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 plugin 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**.
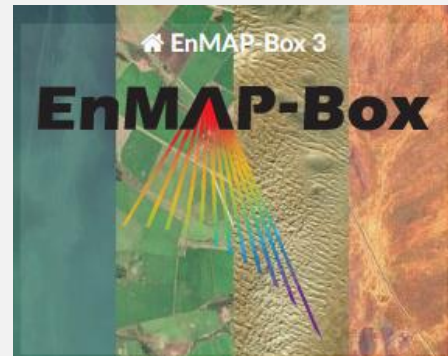
ARTMO

A software package for running and inverting
a suite of plant RTMs, both at the leaf and at
the canopy level, is the in-house developed
**Automated Radiative Transfer Models
Operator (ARTMO)** Graphic User Interface
(GUI): "ARTMO facilitates consistent and intuitive user interaction, thereby streamlining
model setup, running, storing and spectra output plotting for any kind of optical sensor
operating in the visible, near-infrared and shortwave infrared range (400-2500 nm).
ARTMO also hosts the Atmospheric Look-up Generator (ALG) and the Decomposition
and Analysis of Time Series software (DATimeS) as standalone software packages." As
the EnMAP-Box, ARTMO is **available for free**.

Quiz: Data and software resources

Which of the variables below are secondary variables that cannot be inferred directly from imaging spectroscopy data? (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

Spaceborne imaging spectroscopy data is currently freely available from the sensor: (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 pre-processed. And even if the data come processed, it might be helpful to understand the different pre-processing 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.

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

Video URL: https://youtu.be/drqFyMmyPI0

In the basic MOOC, we differentiated between **Classification and Quantification**. Now, we focus on **quantification using regression analysis and radiative transfer modelling (RTM)**. In the following **video**, Charly will give you a general **overview of methods that are widely used in agricultural imaging spectroscopy**.

Video: Agri-06: Imaging Spectroscopy for Agricultural Applications - Regression Models

Video URL: https://youtu.be/TeTyInM23XM
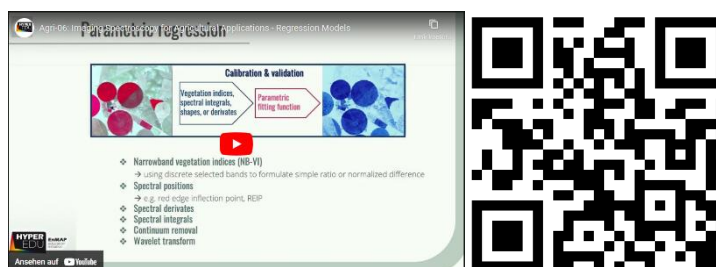
VIDEO: Regression Models

Hang on, what do Hybrid Methods combine? (single choice)

☐   Digital and analogue techniques
☐   Nonparametric methods and radiative transfer models
☐   Parametric Methods and Process Models

Can you recall a popular Parametric Method? (single choice)

☐   Radiative Transfer Models
☐   Machine Learning
☐   Narrow band vegetation indices such as the NDVI

In this course, we want to **focus on hybrid methods** as they combine the flexibility of parametric approaches with the physics encoded in machine learning algorithms. In the following **video**, Charly will be a bit **more specific on** the definition of "**hybrid methods**", what they include and which models are frequently used:

Video: Agri-07: Imaging Spectroscopy for Agricultural Applications - Hybrid Models

Video URL: https://youtu.be/4hIngoVaL9Y
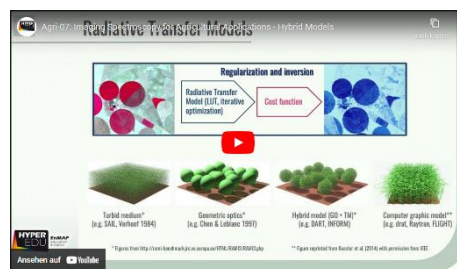
VIDEO: Hybrid Models

The following vegetation variables are often estimated using RTMs. Can you sort them into biochemical and biophysical variables?
yield, leaf area index, leaf chlorophyll content, crop canopy temperature, biomass, leaf nitrogen content, gross primary productivity

Biophysical variables	**Biochemical variables**

We'll be working with them later - Have a guess what lookup tables are (single choice)

☐ A lookup table (LUT) is an array giving an output value for each of a range of index values. The use of LUTs can significantly increase processing time

☐ A lookup table is a tool to validate the output of RTMs by manually comparing the results to values in a predefined table

Quiz: Methods

What does the abbreviation "RTM" stand for in our course context? (single-choice)

☐   Release To Manufacturing

☐   Radiative Transfer Model

☐   Régie des Transport Métropolitains

☐   Requirement Traceability Matrix

Do you recognize popular RTMs in the selection below? (multiple-choice)

☐   PROSPECT

☐   SAIL

☐   PROSAIL

☐   PROPOSAL

Can you match the correct terms?
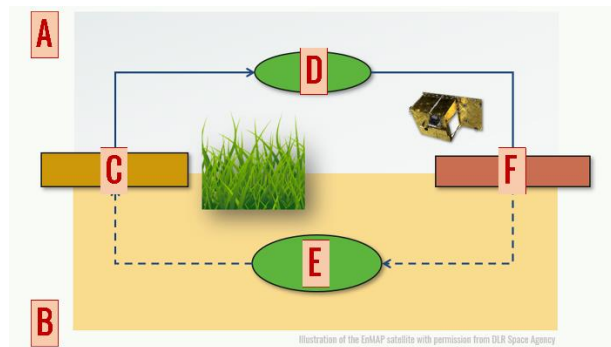
A   Choose an element

B   Choose an element

C   Choose an element

D   Choose an element

E   Choose an element

F   Choose an element

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' 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 agricultural applications in the context of an entire workflow, including 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](#).
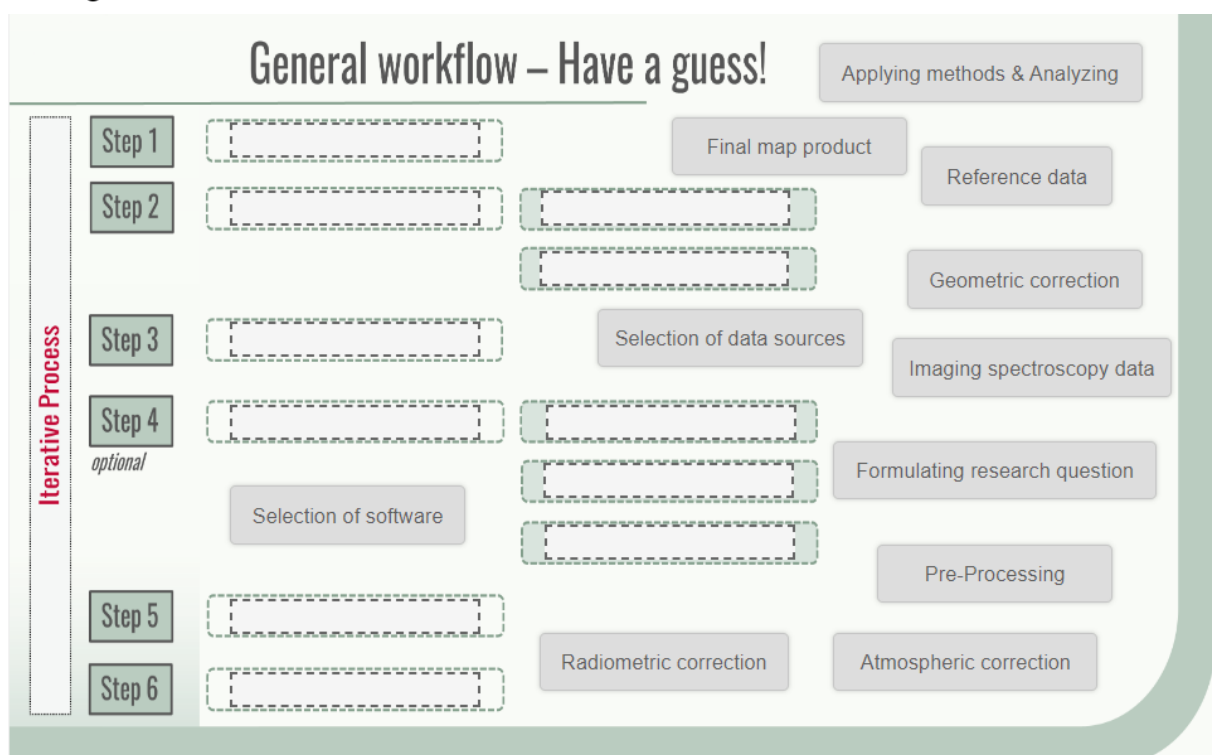
Of course, the workflow shown is very abstract and simplified and you might experience situations where you must iteratively go back and make adjustments. Nevertheless, the exercise shows that the path to a final, qualitative map product based on imaging

spectroscopy data involves many steps whose precise definition requires intensive thought and consideration.

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

Interactive Graphs

Remember: You need to be enrolled and logged in under EO College in order to be forwarded to the interactive Graphs. Figures of those are, however, incorporated in this offline version. For the best learning experience, we recommend to check out the graphs online.

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

4.4 Resources 'Methodological aspects'

In this section, we have assembled resources used for the creation of this lesson that we recommend you use 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).

You can find most figures of this lecture in the HYPERedu slide collection, available on EO-College.

How to cite: K. Berger, J. Verrelst, C. Atzberger, M. Weiss, S. Steinhauser, M. Wocher, S. Foerster, T. Kuester (2020). **Retrieval approaches of vegetation traits from imaging spectroscopy data,** HYPERedu, EnMAP education initiative, September 2020, LMU Munich.

Available in the EO-College hyperspectral resources section: https://eo-college.org/resource/retrieval-approaches-of-vegetation-traits-from-imaging-spectroscopy-data/

Sources for further reading

Topic 1: Data and software

EnMAP Data

www.enmap.org

https://eoweb.dlr.de (in the future)

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. **The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation**. Remote Sens. 2015, 7, 8830-8857. https://doi.org/10.3390/rs70708830

PRISMA Data

http://prisma-i.it

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*

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://artmotoolbox.com/

Topic 2: Methods

Baret, F., Buis, S., 2008. **Estimating canopy characteristics from remote sensing observations: Review of methods and associated problem**s, Advances in land remote Sensing. Springer, Dordrecht, Netherlands, pp. 173-201.

Berger, K., Atzberger, C., Danner, M., D'Urso, G., Mauser, W., Vuolo, F., Hank, T., 2018. **Evaluation of the PROSAIL Model Capabilities for Future Hyperspectral Model Environments: A Review Study**. Remote Sens. 10, 85.

Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P.J., Asner, G.P., François, C., Ustin, S.L., 2009. **PROSPECT + SAIL models: A review of use for vegetation characterization**. Remote Sens. Environ. 113, Supplement 1, S56-S66.

Li, S., Song, W., Fang, L., Chen, Y., Ghamisi, P., Benediktsson, J., 2019. **Deep Learning for Hyperspectral Image Classification: An Overview**. IEEE Trans. Geosci. Remote Sens. PP, 1-20.

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., Johnson, B.A., 2019. **Deep learning in remote sensing applications: A meta-analysis and review**. Isprs J. Photogramm. 152, 166-177.

Verrelst, J., Camps-Valls, G., Muñoz-Marí, J., Rivera, J.P., Veroustraete, F., Clevers, J.G.P.W., Moreno, J., 2015. **Optical remote sensing and the retrieval of terrestrial vegetation bio-geophysical properties – A review**. Isprs J. Photogramm. 108, 273-290.

Verrelst, J., Malenovský, Z., Van der Tol, C. et al. (2019): **Quantifying Vegetation Biophysical Variables from Imaging Spectroscopy Data: A Review on Retrieval Methods**. Surveys in Geophysics. 40, 589–629. https://doi.org/10.1007/s10712-018-9478-y

Weiss, M., Jacob, F., Duveiller, G., 2020. **Remote sensing for agricultural applications: A meta-review**. Remote Sens. Environ. 236, 111402.

Xue, J., Su, B., 2017. **Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications**. Journal of Sensors 2017, 1353691.

Topic 3: Workflow

Bioucas-Dias, J.M., Plaza, A., Camps-Valls, G., Scheunders, P., Nasrabadi, N., Chanussot, J. (2013): **Hyperspectral remote sensing data analysis and future challenges**. IEEE Geosci. Remote Sens. Mag 1(2), 6–36. https://doi.org/10.1109/MGRS.2013.2244672

Ghamisi, P., Yokoya, N., Li, J., Liao, W., Liu, S., Plaza, J., Rasti, B. and Plaza, A. (2017): **Advances in Hyperspectral Image and Signal Processing: A Comprehensive Overview of the State of the Art**. IEEE Geoscience and Remote Sensing Magazine, vol. 5, no. 4, pp. 37-78, Dec. 2017, https://doi.org/10.1109/MGRS.2017.2762087

Li, J., Plaza, A. (2016): **Hyperspectral Image Processing. Methods and Approaches. In: Thenkabail, P.S. (Ed): Remotely Sensed Data Characterization, Classification and Accuracies**. Taylor and Francis group. https://www.umbc.edu/rssipl/people/aplaza/Papers/BookChapters/2016.Handbook.Hyperspectral.pdf

Lillesand T., Kiefer R.W. & J. Chipman (2008): **Remote Sensing and Image Interpretation. 6th Edition, Wiley.**

Schowengerdt (2007): **Remote Sensing: Models and Methods for Image Processing**. 3rd Edition, Elsevier

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 courseCosmetic correction

☐   From Guanter et al. 2015

What does the "A" in "Aviris NG" stand for? (single-choice)

☐   Average

☐   Airborne

☐   Advanced

☐   Avenger

Which bands does the GNDVI index use (if you are not sure, check the index database https://www.indexdatabase.de/db/i.php) (single-choice)

☐   NIR and RED

☐   NIR and GREEN

☐   NIR, RED and GREEN

☐   NIR, RED, GREEN and BLUE

If you want to vizualise hyperspectral data, you can do so for FREE 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

The two spectra below show a vegetation spectrum before and after atmospheric correct was applied. Click on the one without atmospheric correction? (single-choice)

☐

☐
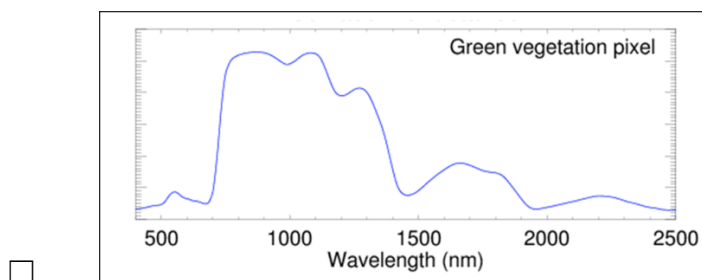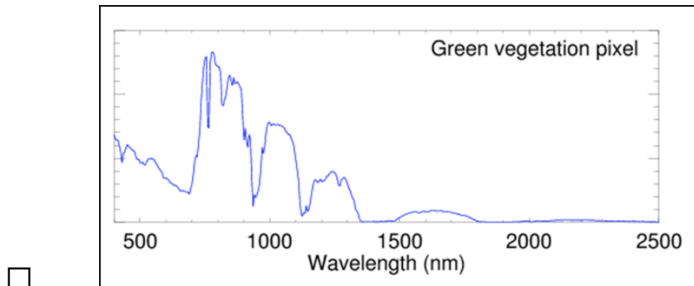
Why is geometric correction important? (multiple-choice)

☐ 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)

What are "hybrid models"? (single-choice)

☐ They involve the visual interpretation of an image and can be exercised analogue

☐ They combine radiative transfer modelling and machine learning

☐ They combine non-parametric regression and machine learning

Radiative transfer modelling can be performed … (multiple-choice)

☐   Unfortunately, only by buying expensive and highly specific software
         solutions

☐   Using the EnMAP-Box

☐   Only by developing your own code

☐   Using ARTMO

What is the benefit of combining machine learning and RTMs? (single-choice)

☐   I don't know, I'm just using it because it's said to be state of the art

☐   Combining the flexibility and scalability of ML while respecting the
         physics encoded in the RTM

☐   Practical reasons as most software packages only offer them in
         combination

☐   A tremendous increase in processing speed

Can you match the correct terms?

Illustration of the EnMAP satellite with permission from DLR Space Agency

A   Choose an element

B   Choose an element

C   Choose an element

D   Choose an element

E   Choose an element

F   Choose an element

05. Hands-On training

Welcome to our third lesson! The following topics are "hands on", meaning you can actively participate in the exercises that we designed specifically for this course! The software and 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 result we strongly encourage you to use this opportunity to "get your hands dirty" during some expert-guided hands-on training exercises! As before, Charly will explain the learning objectives of this – final – lesson in the video below.

Video: Agri-08: Imaging Spectroscopy for Agricultural Applications - Lesson 05 Intro

Video URL: https://youtu.be/D5r52IfnM3g

Please feel free to point out further resources in the discussion forum. You can find the discussion forum at https://eo-college.org/forums/forum/beyond-the-visible/agricultural-applications/ under each related topic.

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 "Agricultural Apps" to learn how to retrieve quantitative biophysical and agriculturally relevant information from hyperspectral data. In case you have the EnMAP Box already installed and are familiar with the visualization tools, you can skip the rest of 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

Video URL: https://youtu.be/_SNbLmB8aCQ

Data visualization

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

Video URL: https://youtu.be/qVoi0CoJheI

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

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 a 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 Agricultural Apps

Okay, here we go. In the following screencasts, we will show you step by step how to get acquainted with the data and produce a training database, how to train a machine learning algorithm, retrieve quantitative information and lastly, how to validate your results.

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

Get acquainted with the data and produce a synthetic training database

Video: Agri-09: Get acquainted with the data and produce a synthetic training database

Video URL: https://youtu.be/QIjv3mSaAYw
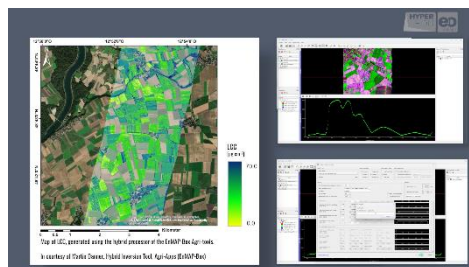
Train a machine learning algorithm

Video: Agri-10: Train a machine learning algorithm

Video URL: https://youtu.be/nwssbxgjNK0
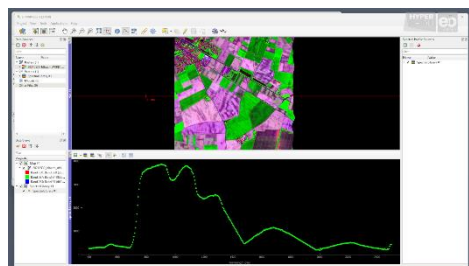
Retrieve quantitative information with a hybrid model

Video: Agri-11: Retrieve quantitative information with a hybrid model

Video URL: https://youtu.be/sTz87-OqYwg
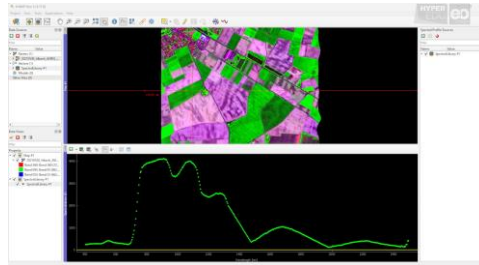
Validate your retrieval results with in-situ data

Video: Agri-12: Validate your retrieval results with in-situ data

Video URL: https://youtu.be/GMPeit4qRT4
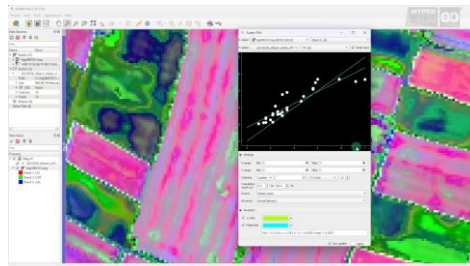
You might find that your results differ from Tobis. Don't worry, that's normal and we can explain why: On the one hand, this is due to the fact that while the training database (the LUT file) is compiled according to the same statistical criteria, the dice are rolled anew each time you run the tool and the resulting training database can be very different, despite identical parameterization. Another deviation can happen when training the model, because the ANN does not necessarily pick the same data out of the training dataset each time. And finally, numerical uncertainties can occur when inverting the ANN (though they should be rather small in comparison).

Quiz: EnMAP-Box Agricultural Apps

In the exercise, we are working with a scene acquired by which sensor? (single-choice)

☐   AVIRIS

☐   EnMAP

☐   AVIRIS NG

☐   PRISMA

In the list of leaf model parameters below, there is one that you CANNOT set directly in the creation of your training data base BUT knowledge about this parameter might help in defining the other parameters more accurately. Which parameter is it? (single-choice)

☐   Chlorophyll A + B (Cab)

☐   Phenology

☐   Dry Matter Content (Cm)

☐   Water Content (Cw)

5.3 Discussion of accuracy and limitations

In the previous exercise, we retrieved quantitative information from a hyperspectral image and validated our result using some in-situ measurements. But how accurate are the results?

Well, there are several aspects to consider. For one, 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. Plus, despite our best efforts, the spatial scale in the field is different from air- or spaceborne resolution. Actually, this aspect of uncertainty is often neglected in studies dealing with the comparison of remotely measured and field sampled data: Some variables are traditionally measured in the field at the leaf level, while airborne or spaceborne sensors, especially when they scan the Earth's surface at nadir view, observe the canopy as a whole. For example, biochemicals such as chlorophyll, nitrogen, anthocyanins, water etc. may occur in very different concentrations in the various parts of a plant (roots, stems, leaves, ears) and may also show vertical gradients (e.g. senescence starts near the ground and gradually approaches the top of the canopy). Unfortunately, many of the field instruments that are used to sample these variables are easily be applied to leaves, but are not suited to measure the canopy as a whole (e.g. the SPAD Chlorophyll meter). The hyperspectral instrument observing the canopy from above, in contrast, is not able to discern between the signals emerging from leaves stems and ears, but rather integrates across the top of the canopy according to its point spread function. Comparing the quantities measured on the ground at leaf level and maybe also in the middle level of the canopy with the quantities derived from the hyperspectral signal at top of canopy level will inevitably lead to poor agreement.

So, **how can we quantify uncertainty**? Reichstein and colleagues (2019) said that "Models [themselves] should define their confidence and credibility" and Malenovsky et al. (2019) stated that "Validation of vegetation traits retrieved from optical remotely sensed data is an essential part of the estimation process indicating its fidelity." In our exercise, we quantified **physical uncertainties** that indicate the deviations of retrieval products from "hypothetically true" values collected in situ during ground campaigns, as this is pretty straightforward. In cases where no in situ data are available – or ideally in addition to the physical uncertainties- you can quantify **theoretical uncertainties**, by using either spectral residuals or standard deviations, OR the likelihood of values estimated in frame of statistical fuzzy approaches such as Bayesian methods.

Uncertainty regarding in situ measurements of a validation site is related to the intrinsic natural variability of vegetation traits in space and time, and to the nature of the measurement method. The graph shows the hypothetical validation of imaging spectroscopy based estimates for five virtual validation sites.

"The measurement and the estimation uncertainties, driven by actual precision and accuracy, are presented as a purple ellipse. In all

Figure 23 **The quantification of uncertainty**. Berger et al. (2021): Retrieval approaches of vegetation traits from imaging spectroscopy data

cases, the uncertainty in ground-*truth* measurements is expected to be smaller than the uncertainty of a corresponding estimate. Hence, the measurement uncertainty is given by an ellipse on the minor axis and the uncertainty of an estimate is given by its major axis. Horizontal black arrows show a natural within-site variability of a given parameter, while grey zones illustrate variability captured in validation measurements collected at a given Validation site. The dashed line indicates the one-to-one line, i.e. the expected best fit between measured and estimated values." For interpretation of the five validation sites, please refer to Malenovský et al (2019).

Some hybrid methods incorporate the assessment of uncertainties. Below, is an example of the Gaussian Process (GP)-based retrieval of canopy nitrogen content as implemented in ARTMO. Nitrogen content is displayed in orange-green gradients, whereas the blue coloured maps indicate absolute uncertainties (=standard deviations), which are directly related to the magnitude of the mean estimates. Probability density plots of the crops can be used to check plausibility of the variable distribution (though they provide no real quantification of the absolute estimation accuracy of the respective variables, even if the model is very plausible the model decision can still be wrong). GPR is a fast and accurate nonlinear retrieval algorithm that can potentially be implemented for operational N monitoring applications.
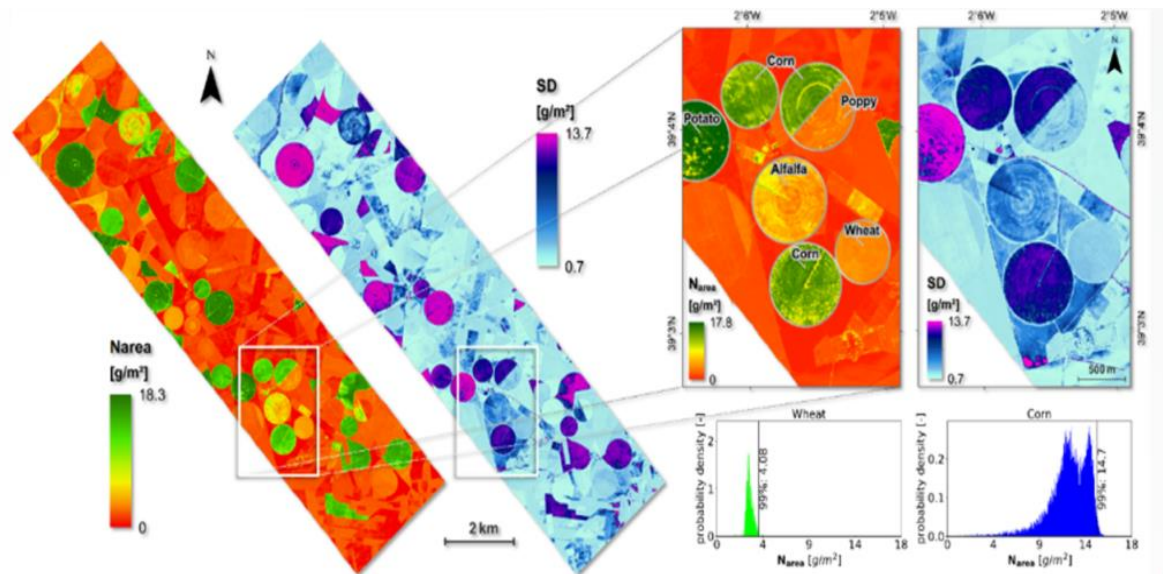
Figure 24 **Gaussian processes for uncertainty estimates.**
Reprinted from Berger et al. 2020 with permission from Elsevier

Quiz: Discussion of accuracy and limitations

How can we quantify uncertainties? (multiple-choice)

☐ Physical uncertainties indicate the deviations of retrieval products from "hypothetically true" values collected in situ during ground campaigns

☐ Physical uncertainties are used when no in situ data are available, e.g. via spectral residuals or standard deviations

☐ Theoretical uncertainties indicate the deviations of retrieval products from "hypothetically true" values collected in situ during ground campaigns

☐ Theoretical uncertainties are used when no in situ data are available, e.g. via spectral residuals or standard deviations

Which colour gradient indicates the crop nitrogen content of the previously shown maps? (single-choice)

☐ orange-green

☐ shades of blue

☐ black and white

5.4 Resources section 'Hands-On training'

In this section, we have assembled resources used for the creation of this lesson that we recommend you use 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).

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Sources for 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: Introduction to the EnMAP-Box

> General information on the "Agricultural Apps" toolbox and guidance on how to apply the individual tool: https://enmap-box-lmu-vegetation-apps.readthedocs.io/en/latest/

Topic 3: Discussion of accuracy and limitations

> Berger, K., Verrelst, J., Féret, J.-B., Hank, T., Wocher, M., Mauser, W., Camp-Valls, G. (2020). **Retrieval of aboveground crop nitrogen content with a hybrid machine learning method**. International Journal of Applied Earth Observation and Geoinformation, 92.

> Cooper, G.F., Herskovits, E., 1992. **A Bayesian method for the induction of probabilistic networks from data**. Machine Learning 9, 309-347.

> Danner, M., Wocher, M., Berger, K., Mauser, W., and T. Hank (2018): **Developing a Sandbox Environment for Prosail**, Suitable for Education and Research, IGARSS 2018 – 2018 IEEE

International Geoscience and Remote Sensing Symposium, pp. 783-786, doi: https://ieeexplore.ieee.org/document/8519378

Danner, M., Wocher, M., Berger, K., Mauser, W. & Hank, T. (2021): **Efficient training of machine learning regression algorithms to quantify biophysical & biochemical traits of agricultural crops**. ISPRS Journal of Photogrammetry and Remote Sensing. Volume 173, pp. 278-296, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2021.01.017.

Hank, T., Berger, K., Wocher, M., Danner, M. and W. Mauser (2021): **Introducing the Potential of the EnMAP-Box for Agricultural Applications Using Desis and Prisma Data**, 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, pp. 467-470, doi: https://ieeexplore.ieee.org/document/9554729

Malenovský, Z., Homolová, L., Lukeš, P., Buddenbaum, H., Verrelst, J., Alonso, L., Schaepman, M.E., Lauret, N., Gastellu-Etchegorry, J.-P., 2019. **Variability and Uncertainty Challenges in Scaling Imaging Spectroscopy Retrievals and Validations from Leaves Up to Vegetation Canopies**. Surv. Geophys. 40, 631-656.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., Prabhat, M., 2019. **Deep learning and process understanding for data-driven Earth system science**. Nature 566, 195.

Rivera, J., Verrelst, J., Leonenko, G., Moreno, J., 2013. **Multiple Cost Functions and Regularization Options for Improved Retrieval of Leaf Chlorophyll Content and LAI through Inversion of the PROSAIL Model**. Remote Sens. 5, 3280-3304.

Verrelst, J., Rivera, J.P., Moreno, J., Camps-Valls, G., 2013. **Gaussian processes uncertainty estimates in experimental Sentinel-2 LAI and leaf chlorophyll content retrieval**. Isprs J. Photogramm. 86, 157-167.

Wocher, M., Danner, M., Berger, K., Mauser, W. & Hank, T. (2018): **Physically-Based Retrieval of Canopy Equivalent Water Thickness Using Hyperspectral Data**. Remote Sensing 10 (12), 1924; https://doi.org/10.3390/rs10121924.

Wocher, M., Berger, K., Danner, M., Mauser, W. & Hank, T. (2020): **RTM-based dynamic absorption integrals for the retrieval of biochemical vegetation traits**. International Journal of Applied Earth Observations and Geoinformation, Volume 93, December 2020, 102219, https://doi.org/10.1016/j.jag.2020.102219

Quiz: Hands-on Training

To generate a training data base that will be large and diverse enough to satisfy the needs of our machine learning algorithm, we ... (single-choice)

☐   ... we first need to create Endmembers to populate the training data base with combinations of reflectance signatures and corresponding model parameters

☐   ... we first need to create a Look-Up-Table to populate the training data base with combinations of reflectance signatures and corresponding model parameters

☐   ... we first need to create a Look-Up-Table to establish nonlinear relationships between our field and image data

The training data base that we created in the hands-on exercise contained reflectance signatures of ... (multiple-choice)

☐   Vegetation

☐   Soil

☐   Water

☐   Air

Before training our machine learning algorithm, we first perform a Principal Component Analysis or PCA. Why? (multiple-choice)

☐   To reduce the dimensionality of our data

☐   To add some bands containing additional information

☐   Because the "Agricultural Apps" cannot handle more than 10 reflectance spectra

☐   Because some machine learners do not perform very well when they are flooded with the large dimensionality of original hyperspectral data

In our example, the machine learning algorithm consisted of an artificial neural network (ANN). What was the ANN trained on? (single-choice)

☐   Training data that we collected in the field (as shown in Lesson 4)

☐   Endmembers (EM) that were collected from the image

☐   A Look Up Table (LUT)

☐   ANNs don't need to be trained

To retrieve quantitative information from our hyperspectral image …? (single-choice)

☐   … we run our trained model (the ANN) in inverse mode

☐   … we run our trained model (the ANN) in forward mode

☐   … we perform a classification

In the Canopy Model Parameters settings, you need to set several angles. What do they correspond to? (single-choice)

Observation Zenith Angle	Choose an element
Sun Zenith Angle	Choose an element
Relative azimuth Angle	Choose an element

What are advantages of hybrid models? (multiple-choice)

☐   They combine the flexibility and scalability of machine learning while respecting the physics encoded in Radiative Transfer Models

☐   They establish nonlinear relationships between any kind of data without the incorporation of physical rules

☐   They achieve high accuracy results even if no field data is available for training

☐   They are the fastest and easiest method to get information from hyperspectral data

How many field samples do you need to run a hybrid model for 100 ha of farmland? (single-choice)

☐　　　　Actually 0 but some would be handy for the validation of results

☐　　　　No more than 10

☐　　　　Between 10 and 100

☐　　　　100, as a minimum of 1 sample per hectare is required to run a hybrid model

Which aspect of uncertainty is often neglected in the comparison of remotely measured and field sampled data? (multiple-choice)

☐　　　　Some variables are traditionally measured in the field at leaf level, while airborne or spaceborne sensors observe the canopy as a whole

☐　　　　This applies to parameter such as the leaf area index (LAI)

☐　　　　The uncertainty in hybrid model output is minor so that it actually CAN be neglected

☐　　　　This applies to biochemicals such as chlorophyll, nitrogen and anthocyanins

In cases where no in situ data are available – or ideally in addition to the physical uncertainties – you can quantify theoretical uncertainties, by … (multiple-choice)

☐　　　　… drawing lines and ellipses in your scatter plots

☐　　　　… using spectral residuals or standard deviations

☐　　　　… using the likelihood of values estimated in frame of statistical fuzzy approaches such as Bayesian methods

☐　　　　… discussing the model parameterization

6 Goodbye!

Well done! You've learned a lot about imaging spectroscopy for agricultural applications. **Let's move on with the final survey**! The survey helps us to improve this course as well as future ones and will take you about 2 minutes. Afterwards it will get serious…we want to test your knowledge with the Final Quiz!

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. You can access the final user survey under the following Link.

If you have any further suggestions, please let us know vie email or through the **discussion forum**.

6.2 Final Exam

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

Oh … and don't forget to say goodbye and check out our incredible team!

Quiz: Final Exam

With decreasing LAI, the spectrum of green vegetation … (multiple-choice)

☐   … becomes increasingly flat (less pronounced absorption features)

☐   … remains the same except for changes in the VIS region

☐   … becomes increasingly more similar to a soil spectrum

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

Assign the correct surface material to its respective spectral signature
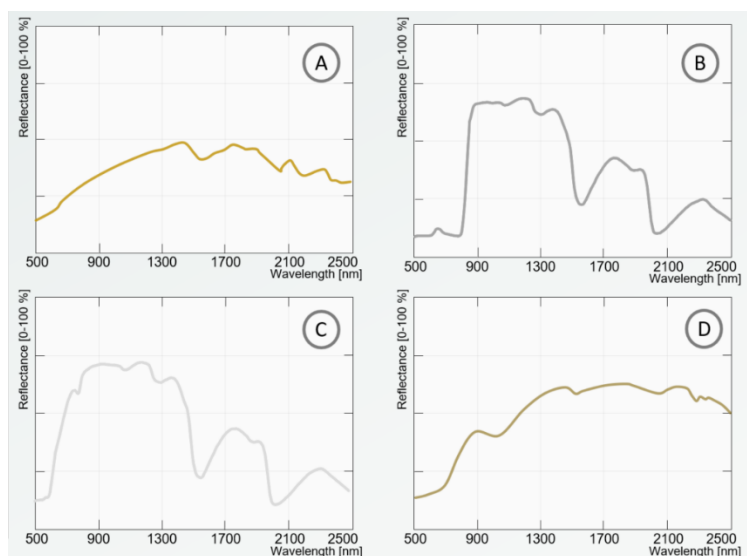
A   Choose an element

B   Choose an element

C   Choose an element

D   Choose an element

With respect to vegetation traits, what are "primary variables"?... (multiple-choice)

☐   Variables that are most important for agricultural 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 is the difference between leaf and canopy traits? (multiple-choice)

☐   Leaf level traits can only be assessed in the laboratory while canopy
          level traits can be assessed in the field

☐   Leaf level traits describe the biochemical and morphological properties
          of leaves while canopy level traits mainly describe the structural
          properties of a vegetation stand

☐   While the majority of leaf level traits rely on parametric regressions,
          canopy level traits are often retrieved using machine learning
          approaches

☐   In fact, there is not really a difference

Which of the variables below are secondary variables that cannot be inferred directly
from imaging spectroscopy data? (multiple-choice)

☐   Nitrogen content

☐   Phenology

☐   Pigment content

☐   Irrigation needs

If you want to vizualise hyperspectral data, you can do so for FREE 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

What are "hybrid models"? (single-choice)

☐   They involve the visual interpretation of an image and can be exercised analogue

☐   They combine radiative transfer modelling and machine learning

☐   They combine non-parametric regression and machine learning

What is the benefit of combining machine learning and RTMs? (single-choice)

☐   I don't know, I'm just using it because it's said to be state of the art

☐   Combining the flexibility and scalability of ML while respecting the physics encoded in the RTM

☐   Practical reasons as most software packages only offer them in combination

☐   A tremendous increase in processing speed

To generate a training data base that will be large and diverse enough to satisfy the needs of our machine learning algorithm, we … (single-choice)

☐   … we first need to create Endmembers to populate the training data base with combinations of reflectance signatures and corresponding model parameters

☐   … we first need to create a Look-Up-Table to populate the training data base with combinations of reflectance signatures and corresponding model parameters

☐   … we first need to create a Look-Up-Table to establish nonlinear relationships between our field and image data

Before training our machine learning algorithm, we first perform a Principal Component Analysis or PCA. Why? (multiple-choice)

☐   To reduce the dimensionality of our data

☐   To add some bands containing additional information

☐   Because the "Agricultural Apps" cannot handle more than 10 reflectance spectra

☐   Because some machine learners do not perform very well when they are flooded with the large dimensionality of original hyperspectral data

To retrieve quantitative information from our hyperspectral image … (single-choice)

☐   … we run our trained model (the ANN) in inverse mode

☐   … we run our trained model (the ANN) in forward mode

☐   … we perform a classification

The results retrieved with the methodology we showed in lesson 5 can differ every time you run the model. Why? (multiple-choice)

☐   This can happen when training the model, because the ANN does not necessarily pick the same samples out of the training dataset each time.

☐   This can be due to numerical uncertainties that can occur when inverting the ANN.

☐   This can be due to the fact that the dice are rolled anew each time you create a lookup table (.lut file) and the resulting training database can be very different, despite identical parameterization.

☐   This can happen when you don't pay attention during training database and/or model parameterization.

How can uncertainty be quantified in cases where no in situ data are available? (multiple-choice)

☐   By discussing the model parameterization

☐   By using spectral residuals or standard deviations

☐   Without ground reference data the uncertainty of maps from remote sensing data can only be described qualitatively

☐   By using the likelihood of values estimated in frame of statistical fuzzy approaches such as Bayesian methods

Why do we call in situ measurements "ground reference" but not "ground truth"? (multiple-choice)

☐   Actually, we do call them ground truth as they represent perfectly correct values

☐   Because ground reference data is never entirely "true", mistakes can happen during measurement and analyses

☐   Because ground reference data is never entirely "true" as some variables are highly variable in space and time

☐   Because we want to promote the use of remote sensing products and the term "ground truth" makes the maps appear less reliable

6.3 Goodbye!

Thank you for completing the entire MOOC on hyperspectral remote sensing for agricultural applications! We hope you had as much fun in participating as we did in 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 …

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.
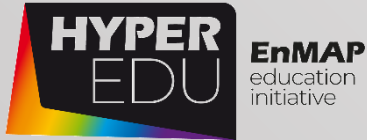
MOOC Document

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