HYPER EDU EnMAP education initiative

MOOC Document

Beyond the Visible – Imaging Spectroscopy for Forest Applications

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List of Abbreviations

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

AI: Artificial Intelligence

ALIA: Average Leaf Inclination Angle

ALG: Atmospheric Look-up Generator

APAR: Absorbed Photosynthetically Active Radiation

API: Application Programming Interface

ARTMO: Automated Radiative Transfer Models Operator

ARES: Airborne Research Facility for the Earth System

ASI: Italian Space Agency

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

C_{ab}: chlorophyll a + b

C_{ar}: carotenoid

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

DATimeS: Decomposition and Analysis of Time Series software

DLR: German Space Agency

DN: Digital number

EeTeS: EnMAP end-to-end simulator

EnMAP: Germany's Environmental Mapping and Analysis Program

ENVI: Environment for Visualizing Images software

ESA: European Space Agency

EU: European Union

EWT: Equivalent Water Thickness

FAO: Food and Agriculture Organization of the United Nations

FRA: Global Forest Resources Assessment

GFZ: German Research Center for Geosciences (Potsdam)

GIS: Geographic Information System

GSA: Global Sensitivity Analysis

ICRAF: International Council for Research in Agroforestry

LAD: Leaf Inclination Angle Distribution

LAI: Leaf Area Index

LCC: Leaf Chlorophyll Content

LED: Light Emitting Diode

LiDAR: Light Detection and Ranging

LIDF: Leaf Angle Distribution Function

LULUCF: Land Use, Land Use Change and Forestry

MIR: Mid infrared

MOOC: Massive open online course

NASA: National Aeronautics and Space Administration

NDI: Normalized Difference Index

NDVI: Normalized Difference Vegetation Index

NFIs: National Forest Inventories

NIR: Near-infrared

NN: Neural Networks

NPP: Net Primary Productivity

PCA: Principal Component Analysis

PLSR: Partial-least squares regression

PRI: Photochemical Reflectance Index

PRISMA: PRecursore IperSpettrale della Missione Applicativa

RF: Random Forest

RTM: Radiative Transfer Model

SAR: Synthetic-aperture radar

SBG: NASA's Surface Biology and Geology Investigation Mission

SPAD: Single-Photon Avalanche Diode

SVM: Support Vector Machine

SWIR: Short wave infrared

TIR: Thermal infrared

TUB: Technical University of Berlin

UAV: Unmanned Aerial Vehicles

UV: Ultraviolet

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 Forest Applications '!*

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

The first lesson is accessible to everyone – here, you can meet your instructors and they will explain the benefits of hyperspectral remote sensing over other types of remote sensing data, as well as the challenges and opportunities for applications in a forest context. Plus, you can 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 very basics of hyperspectral remote sensing that you need to pass in order to get access to the rest of the course – this is not to discourage you but to ensure you have sufficient background knowledge to enjoy this MOOC. Don't worry, you have unlimited attempts to pass ...

The third to fifth lessons consist of 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, how data acquisition works in the field (we will be even visiting a large crane located in the middle of a forest!) and which steps are taken in a laboratory to determine certain physiological characteristics. We will also provide you with insights to methodological considerations. The final lesson comprises a hands-on exercise in which you'll be given the chance to download and process hyperspectral imagery yourself!

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

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

- the benefits of imaging spectroscopy for forest applications

- the physical and chemical factors controlling leaf and canopy reflectance in a forest context
- which biophysical and biochemical variables can be retrieved from spectral information
- some insights to campaign- and sampling design for forest applications
- how reference data are acquired in a forest context
- which laboratory measurements are undertaken for forest applications
- where you can get imaging spectroscopy data from and what software you could use
- which methods to apply in a forest context
- and finally, how to analyze an imaging spectroscopy dataset yourself!

Advice - how to get through the course smoothly

This course was designed to be taken from a desktop PC or laptop, though most content should work on a tablet or even 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.

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

VIDEO: Forest-02: Imaging Spectroscopy for Forest Applications - Meet the Teachers

URL of the video https://youtu.be/xjJRHzjQBm4

Let's move on with the first topic **"Hyperspectral remote sensing for forest applications" –** what are you waiting for? Let's go!

1.1 Hyperspectral remote sensing for forest monitoring

Forests play a crucial role in providing a wide range of environmental benefits, including **maintaining biodiversity, regulating climate, and supplying both timber and non-timber products**. However, forest ecosystems are increasingly under threat due to factors like climate change-induced weather extremes, overuse due to population growth, and unsustainable economic exploitation. Key drivers of forest degradation include deforestation for agriculture and development, both legal and illegal logging, drought-related and biological stress, as well as the rising frequency and severity of wildfires (Hill et al., 2019). Abiotic pressures such as droughts, make forests also more vulnerable to pests and diseases. As a result, the provision of key ecosystem services, including carbon storage, water retention, habitat provision and soil avalanche and landslide protection may be significantly diminished (Kirilenko et al., 2007).

The European Union has implemented several policies, including the new **EU Forest Strategy for 2030** (COM, 2021), the **Biodiversity Strategy for 2030** (EC, 2021), the **LULUCF Regulation** (EEA, 2024), and the **EU Timber Regulation** (EP, 2010), all designed to combat deforestation while supporting forest conservation and restoration. In addition to these, in 2023 the European Commission proposed a new law to establish a monitoring framework aimed at enhancing the resilience of European forests. The initiative will offer open access to reliable and up-to-date insights into the condition and developments of forests across the EU. It will draw from and integrate existing national monitoring efforts, while reinforcing the Forest Information System for Europe as a unified database for forest-related data in the region (EC, 2023). These regulations set clear and rigorous objectives, heightening the demand for comprehensive and large-scale forest monitoring.

An efficient forest monitoring should be able to capture climate and human related impacts, including land use changes, forest health declines, and tree mortality leading to loss of carbon stocks. Existing monitoring systems often rely on both ground-based surveys and remote sensing methods. While sample-based field assessments, for example provided by National Forest Inventories (NFIs), provide valuable statistically sound data at comparably large extents (provinces or states), they do not provide spatially continuous information and are hence of limited value for regional monitoring and as input to forest management. Remote sensing offers broad, spatially continuous coverage at comparably fine scale and also across difficult to access areas. It has hence, potential to deliver consistent insights at various spatial and temporal scales. The growing complexity of forest management, balancing ecological preservation with economic interests, requires comprehensive data sources. As a result, remote sensing techniques must address both practical management needs and scientific studies exploring ecological functions (Fassnacht E.F., 2024).

Against this background, **remote sensing** has become an indispensable tool for monitoring forest dynamics. Besides the very prominent role of laser scanning techniques for capturing structural forest information, the growing availability of satellite hyperspectral imagery and advanced image analysis techniques is expected to improve information products related to species composition and health state of forests. While many existing products, such as those from the Copernicus Land Monitoring, have shown to be able to provide reliable information on tree cover and tree mortality, they are not based on hyperspectral data and may have limitations in capturing finer forest properties like the chemical composition of leaves. Besides a dynamic scientific community working on these topics, global initiatives like the FAO's Global Forest Resources Assessment (FRA), and the Global Forest Watch provide data for tracking forest changes, carbon stocks, and land use trends at regional and global scales. These initiatives support transparent, consistent, and timely forest monitoring, helping policymakers and researchers respond more effectively to environmental challenges. In addition, active remote sensing technologies such as LiDAR and SAR further enhance monitoring capabilities by providing detailed information on forest structure, biomass, and canopy dynamics, even under cloud cover or dense vegetation.

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…"

In summary, hyperspectral remote sensing can be useful to derive a variety of forest characteristics, which can help to keep track of vegetation conditions. For example, measuring the content of chlorophyll and other pigments and estimating nutrient and water levels of forests may help to detect stressed forests and thereby contribute to an early detection of calamities. However, only few of these applications are already operational and more research is needed to fully understand the potential of satellite-based hyperspectral remote sensing of forests.

For our MOOC "Beyond the Visible –Hyperspectral Remote Sensing for Forest Applications" **Dr. Michael Förster** (Technische Universität Berlin, Geoinformation in Environmental Planning Lab - Head of vegetation remote sensing) and **Prof. Dr. Fabian Fassnacht** (Frei Universität Berlin, Institute of Geographical Sciences - Head of Remote Sensing and Geoinformatics) discuss the **advantages and current challenges of hyperspectral remote sensing in the context of forest applications** in **the following video**:

VIDEO: Forest-11.2: Expert interview: application field "forest"

URL of the video https://youtu.be/lTEDxnR4hRA

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 know at hyperedu@eo-college.org.

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

How to cite: H. Buddenbaum, J. Hill (2020). Imaging Spectroscopy of Forest Ecosystems - Exploiting the Potential of Hyperspectral Data. HYPERedu, EnMAP education initiative, Trier University; originally published August 2020, revised February 2023.

Available in the EO-College hyperspectral resources section under: https://eo-college.org/resource/imaging-spectroscopy-of-forest-ecosystems/

You can cite this MOOC as: A. Brosinsky, K. Koch, T. Angelopoulou, M. Foerster, F. E. Fassnacht, H. Buddenbaum, P.Kräft, E. A. Schmidt-Riese, O. Özsoy, A. Okujeni (2025). Beyond the Visible – Imaging Spectroscopy for Forest Applications. Massive Open Online Course. HYPERedu, EnMAP education initiative. GFZ Helmholtz Centre for Geosciences; December 2025 . DOI: 10.48440/enmap.2025.001

Hyperspectral remote sensing for forest monitoring

State-of-the-art publications

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- European Commission: Directorate-General for Environment, EU biodiversity strategy for 2030 – Bringing nature back into our lives, Publications Office of the European Union, 2021, https://data.europa.eu/doi/10.2779/677548

- Handbook on the updated **LULUCF Regulation EU 2018/841** - Guidance and orientation for the implementation of the updated regulation - Version 2 https://climate-energy.eea.europa.eu/topics/climate-change-mitigation/land-and-forests/reports/handbook-on-the-update-lulucf-regulation-v2

- Regulation (EU) No 995/2010 of the European Parliament and of the Council of 20 October 2010 **laying down the obligations of operators who place timber and timber products on the market** Text with EEA relevance http://data.europa.eu/eli/reg/2010/995/oj

- **Forest Monitoring, Land Use & Deforestation Trends** | Global Forest Watch https://www.globalforestwatch.org/

- Cover, C. L. (2018). **Copernicus land monitoring service. European Environment Agency (EEA)** https://land.copernicus.eu/en/technical-library/clc-product-user-manual/

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- **FAO's Global Forest Resources Assessment (FRA).** https://www.fao.org/forest-resources-assessment/remote-sensing/fra-2020-remote-sensing-survey/en/

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EnMAP – The German Spaceborne Imaging Spectroscopy Mission

- www.enmap.org

- Chabrillat, S., Foerster, S., Segl, K., Beamish, A., Brell, M., Asadzadeh, S., Milewski, R., Ward, K., Brosinsky, A., Koch, K., Scheffler, D., Guillaso, S., Kokhanovsky, A., Roessner, S., Guanter, L., Kaufmann, H., Pinnel, N., Carmona, E., Storch, T., Hank, T., Berger, K., Wocher, M., Hostert, P., van der Linden, S., Okujeni, A., Janz, A., Jakimow, B., Bracher, A., Soppa, A., M., Alvarado, M., A., L., Buddenbaum, H., Heim, B., Heiden, U., Moreno, J., Ong, O., Bohn, N., Green, O., R., Bachmann, M., Kokaly, R., Schodlok, M., Painter, H., T., Gascon, F., Buongiorno, F., Mottus, M., Brando, E., B., Feilhauer, H., Betz, M., Baur, S., Feckl, R., Schickling, A., Krieger, V., Bock, M., La Porta, L., Fischer, S. (2024). **The EnMAP spaceborne imaging spectroscopy mission: Initial scientific scientific results two years after launch.** Remote Sensing of Environment, 315, 114379. https://doi.org/10.1016/j.rse.2024.114379.

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- 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
- ☐ Green vegetation
- ☐ Dry vegetation
- ☐ Open soil

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

- ☐ Moisture content
- ☐ Species
- ☐ Phenology
- ☐ Health

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

- ☐ Green and red

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

What is a Lambertian surface? (single choice)

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

3. Introduction to imaging spectroscopy for forest applications

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

VIDEO: Forest-03: Imaging Spectroscopy for Forest Applications - Intro Lesson 1

URL of the video https://youtu.be/0KkDC0Mo034

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

3.1 Imaging spectroscopy of forest vegetation (for forest applications)

Overall, absorption characteristics of green vegetation are predominantly similar – that is why, if you have participated in our 'agriculture' MOOC before, the first section of this topic might be largely familiar to you.

As electromagnetic radiation hits a surface, it is partly reflected, absorbed and/or transmitted (Figure 3.1). Thereby, the fractions of absorbed, transmitted and/or reflected radiation vary depending on material and wavelength Remember? This is the basis for remote sensing!

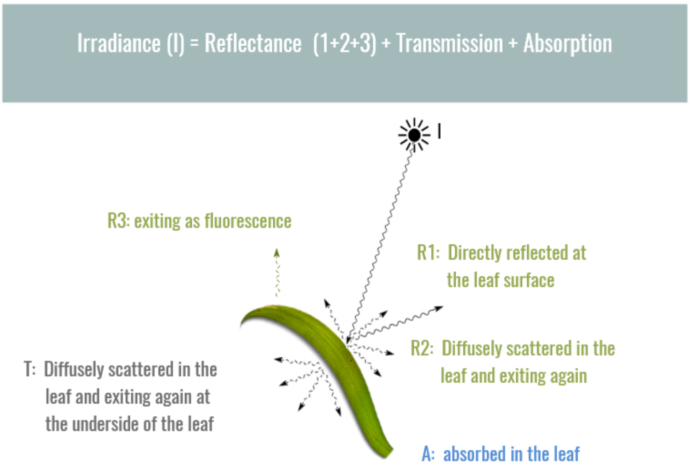


Figure 3.1 Interaction of radiance with leaf.
Adapted from Berger et al. (2021) Spaceborne Imaging Spectroscopy of Agricultural Systems (HYPERedu slide collection)

The radiation penetrating into a leaf is subject to numerous processes like absorption by leaf pigments in chloroplasts, cell water and other leaf constituents (Figure 3.2). 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

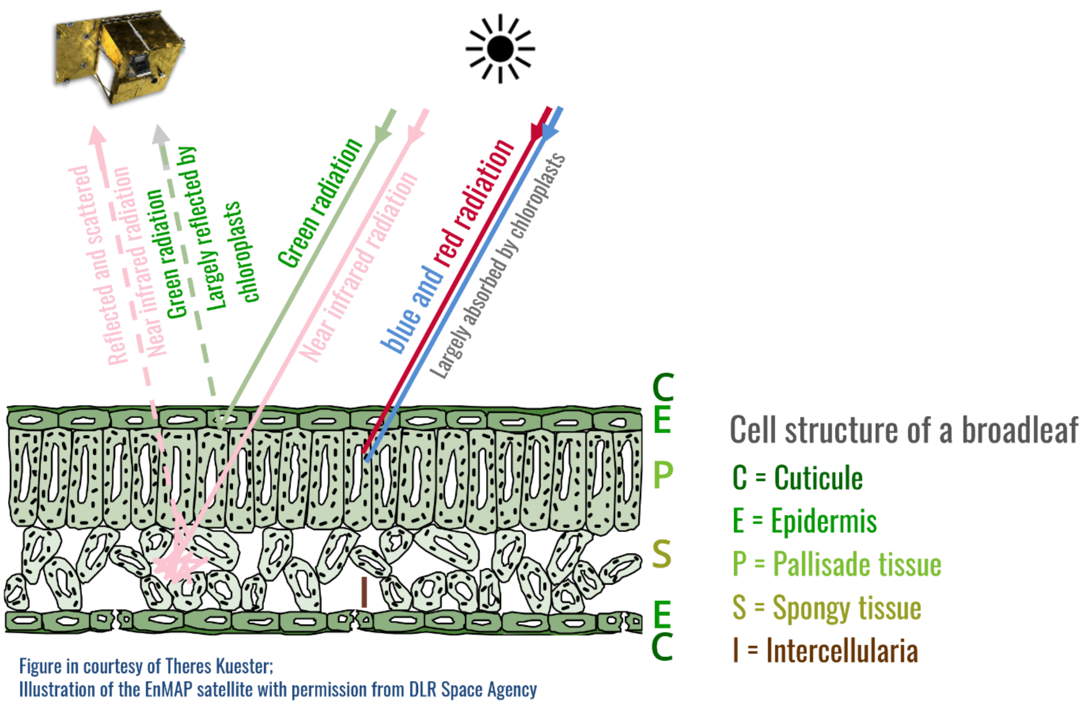


Figure 3.2 Leaf cell structure

In addition to the complex interaction at the leaf level, the interaction with radiance occurs at three scales: In nature, we rarely deal with single leaves but entire plants / trees and therefore need to consider the effect of several leaf layers (Figure 3.3). The leaf surface is the decisive factor 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).

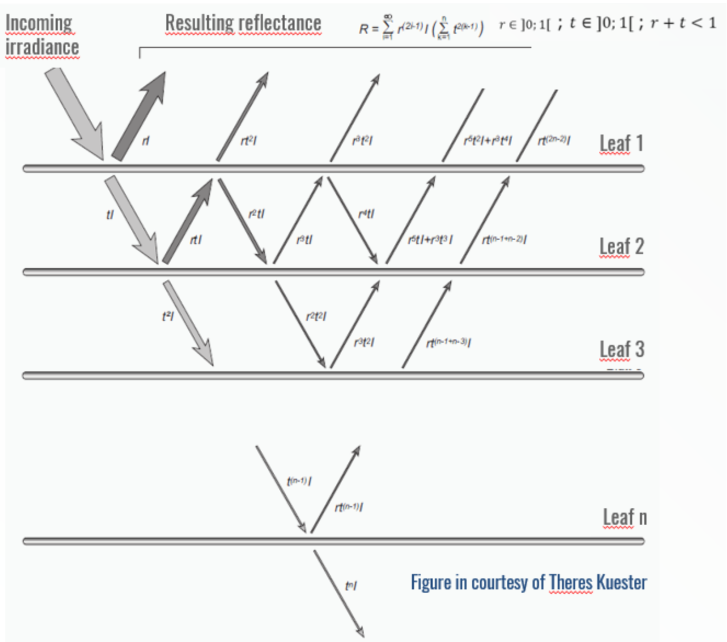


Figure 3.3 Effect of multiple leaf layers

Now, in remote sensing of forests, we generally deal with a number of trees forming a canopy, which is characterized by phytoelements, the phenology and vitality of individuals, the arrangement and density of trees, the species composition, as well as the geometry and reflectivity of undergrowth and soil background (Figure 3.4).

Figure 3.4 Interaction with incoming radiation at three scales (source: FeMoPhys project)

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.

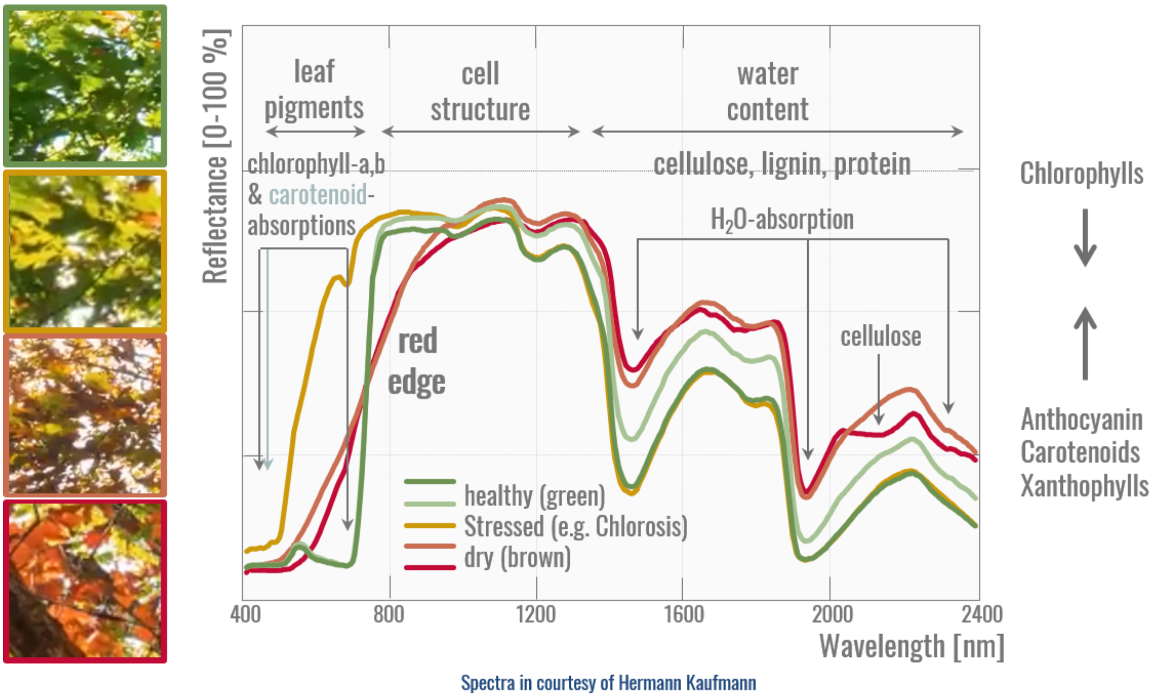


Figure 3.5 Reflectance spectra of green, stressed and drying vegetation

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 (Figure 3.5). 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., by drought or extreme heat, the plants reactions 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.

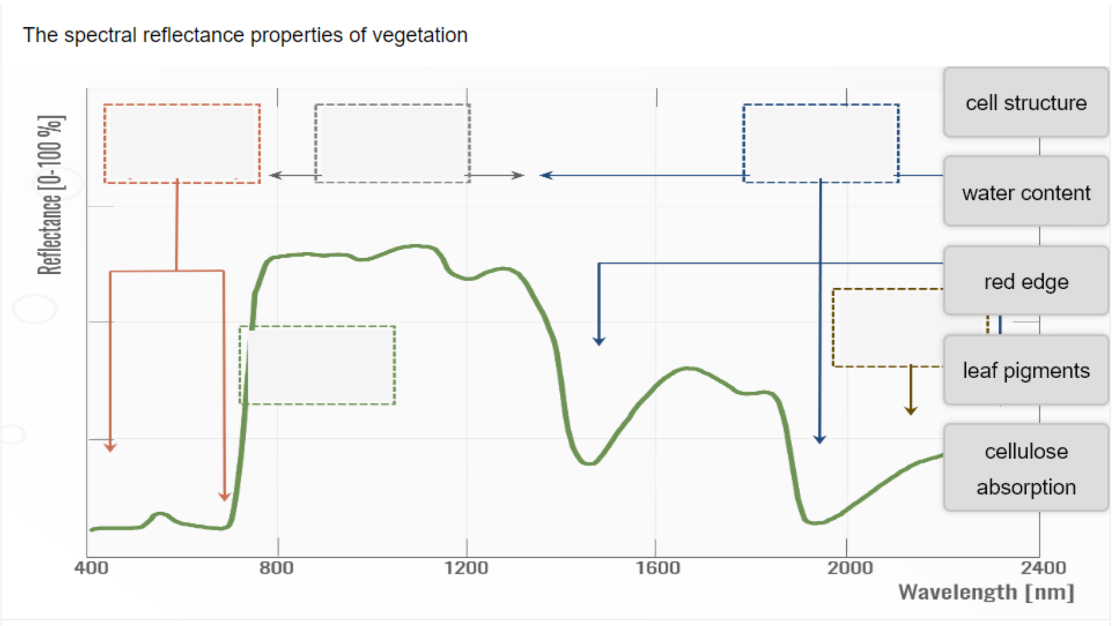
Finally, not only the biochemical composition (e.g., chlorophyll content) but also the biophysical manifestation (e.g., the leaf area index) of vegetation influences the spectral signal. Vegetation is a geometrically complex phenomenon, where **the geometric layout strongly influences the way that light 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.

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.

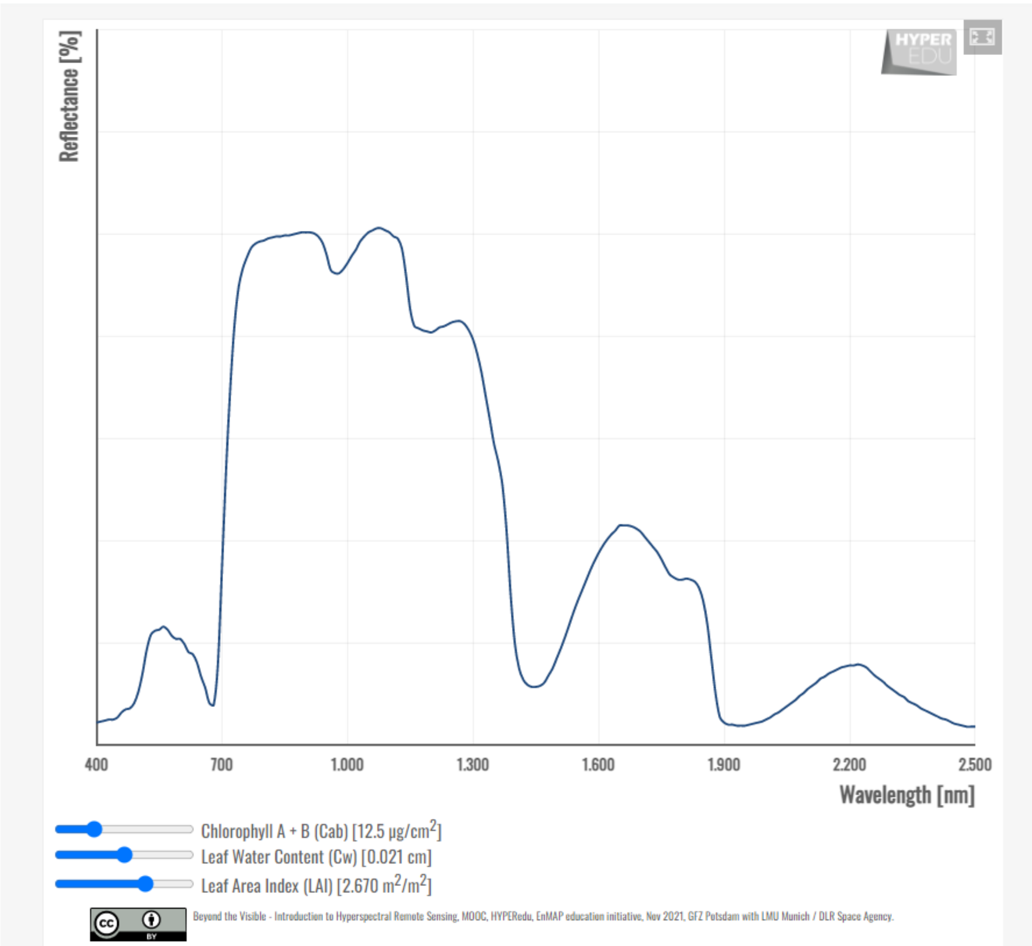
By now, you should be familiar with the spectral reflectance properties of vegetation. Come on, test your knowledge and assign the terms to the spectra below:

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



The interactive graphic below nicely displays how vegetation reflectance changes with changes in leaf chlorophyll and water content as well as LAI. What the graph doesn't show, however, is that vegetation is also partially transparent, especially 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 undergrowth and/or soil will be shining through to some extent. This effect will be less pronounced in dense forests.

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



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:

Quiz: Imaging spectroscopy of vegetation (for forest applications)

Fill in the blanks

Potential answers to fill in the blanks:

- red/ green/ blue
- 550/ 800/ 2200 nm
- cellulose/ chlorophylls/ anthocyanins

The "Click or tap here to enter text.peak" is located around Click or tap here to enter text. nm and caused by the absorption of Click or tap here to enter text..

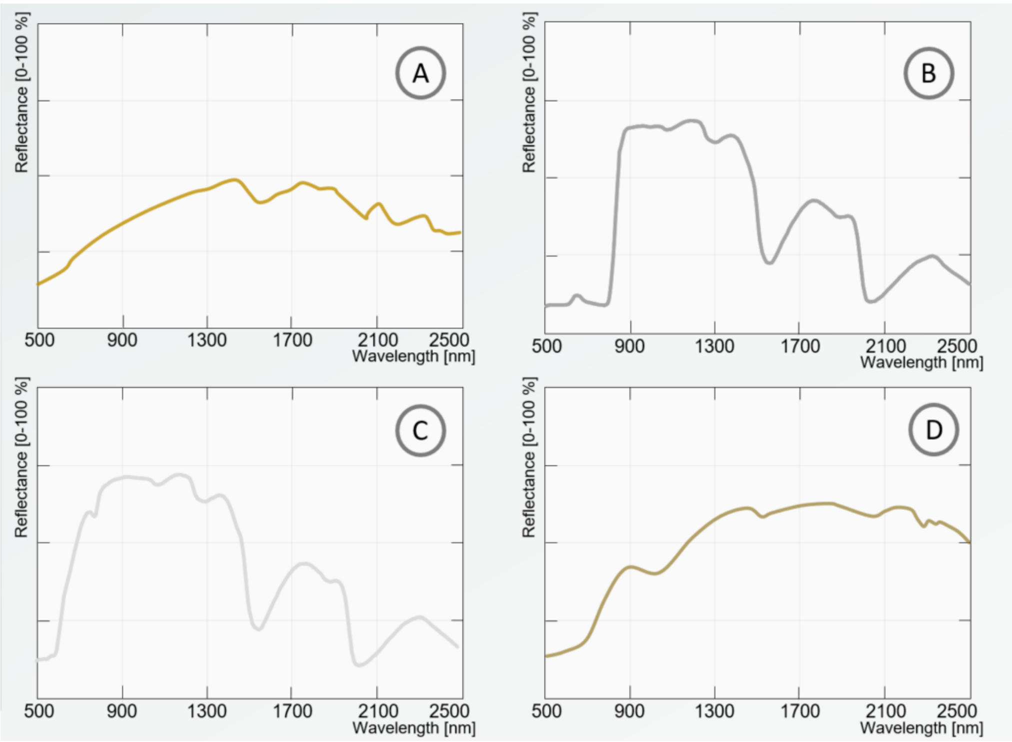
With decreasing LAI, the spectrum of green vegetation ...

☐... 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 the correct surface material to its respective spectral signature:



- ☐ Healthy, green vegetation
- ☐ Dry vegetation
- ☐ Bare soil
- ☐ Stressed, green vegetation

3.2 Variables of interest

Forest reflectance characteristics are determined by many properties, from leaf to canopy level. In this topic, we will provide an overview of the most relevant variables – also called (forestry) traits – that can be predicted using remote sensing data with examples of (spaceborne) hyperspectral imaging. There are several application fields in which imaging spectroscopy can contribute to the understanding of forest ecosystem functioning and thus sustainable forest management. Hill et al. (2019) describe the three key application fields of forestry, in which imaging spectroscopy plays a role, as follows:

One of the most important application areas of imaging spectroscopy is the **detection of biochemical traits and stress** (Hill et al. 2019). Changes in biochemical traits such as the composition and configuration of leaf pigments (e.g. chlorophyll, carotenoids, anthocyanins), water content, as well as cellulose, protein and lignin contents are highly relevant indicators for stress conditions, disturbances or resource limitations. The status of foliar macronutrients (e.g. Nitrogen, Mg, Ca, K, P, S, Mn) assists in the detection of nutrient deficiencies.

Then, imaging spectroscopy certainly has the potential to provide higher classification accuracies for **forest species mapping** than multispectral data, though the spatial resolution of spaceborne sensors may not be sufficient for species identification, but rather mapping of ecological communities (especially in mixed stands) (Hill et al. 2019). The information on tree species composition is important for estimating timber volume and quality, assessing habitat quality and characterizing biodiversity, which is relevant for both conservationists and forest managers.

Forest structural characteristics such as leaf arrangement and geometry, tree height, density, crown size, the shape of forest patches as well as fragmentation and homogeneity are important features of forests that strongly influence the spectral response of forest canopies. In particular, the height of the tree crowns, the extent of the forest and the vertical and horizontal vegetation structure of the forests are important indicators for the assessment of the standing timber volume. While hyperspectral data can be used to estimate forest structure based on texture, the coupling of hyperspectral systems with active remote sensing data such as LiDAR yields much higher accuracies.

With respect to the variables linked to the above categories, we differentiate between leaf level and canopy level variables:

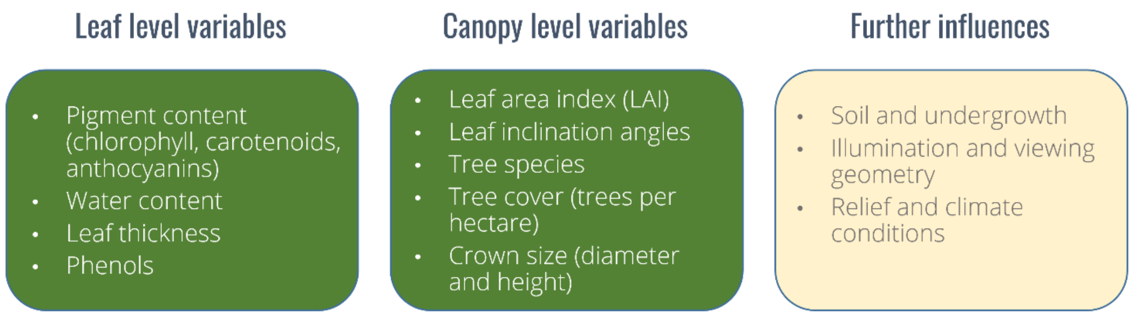


Figure 3.6 Forestry variables at leaf and canopy level

Leaf level variables

Leaf level variables **describe the biochemical and morphological properties of leaves**. These include pigments (e.g. chlorophyll a + b, carotenoids, anthocyanins), phenols, nitrogen, leaf water content, carbon and nonstructural carbohydrates (e.g. starches). **These variables 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 / cm²) or mass-based units (% or mg/g).

Leaf pigments

"Leaf pigments are key components of life on Earth: they are major contributors to individual plant health via complex mechanisms allowing photosynthesis, plant growth, protection, adaptation to environmental changes and phenological events. Their dynamics directly affect nutrient, nitrogen, carbon and water cycles. Leaf pigments are therefore good indicators of changes in environmental conditions from local to global scales." (Féret et al. 2017). Photosynthetic pigments can be used as non-specific indicators of the actual tree physiological status, stress and the pre-visible tree damage (Kopačková et al. 2014).

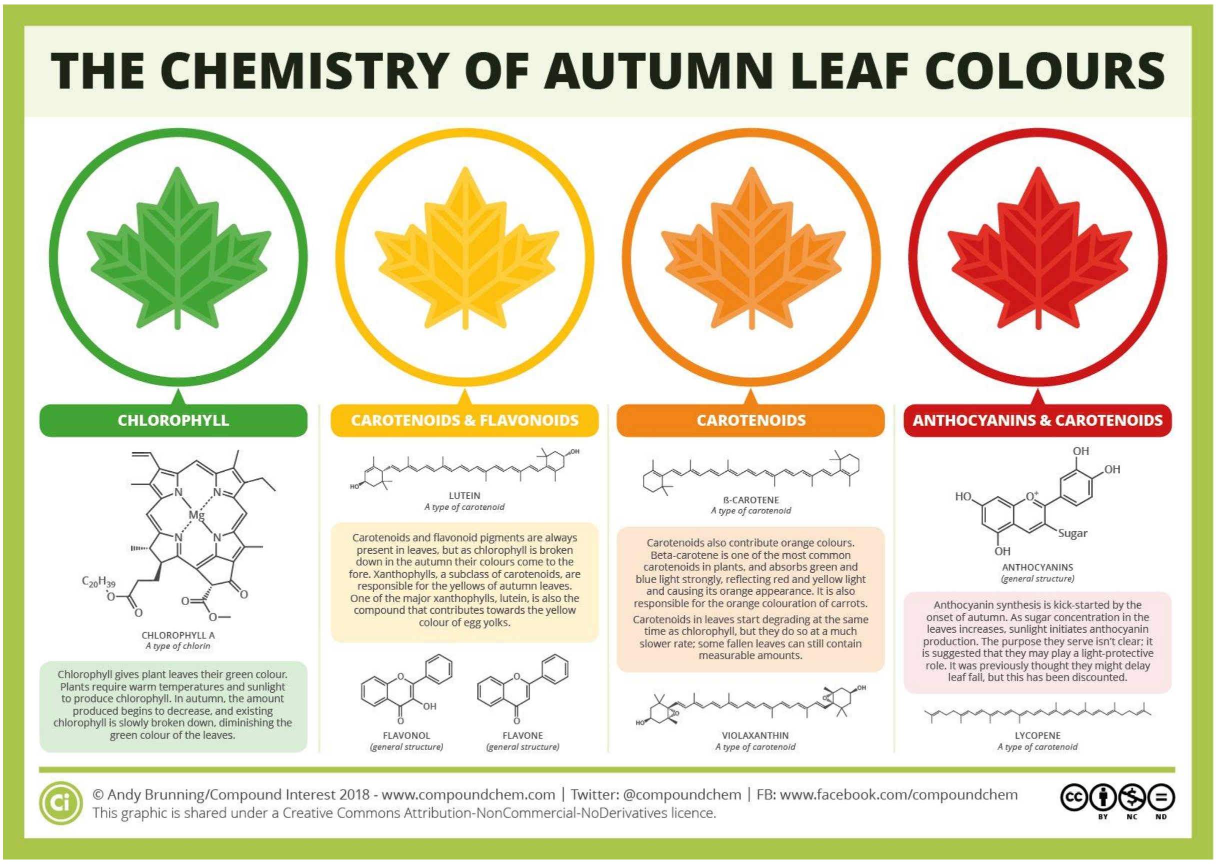


Figure 3.7 The chemistry of autumn leaf colors

Leaf chlorophyll content

Chlorophyll-a and -b, the two types of chlorophyll molecules in higher plants, are the fundamental light-absorbing pigments involved in photosynthesis (Féret et al. 2017), allowing the conversion of absorbed solar irradiance into stored chemical energy. 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 limits the photosynthetic capacity and reduces primary productivity of plants.
Collecting leaves from mature trees can be challenging … branches are often fetched by tree climbers or shot down, e.g., with a crossbow.

Leaf chlorophyll content is usually quantified in units of µg chlorophyll per cm^2 (leaf area), or µmol cm^{-2} or µg g^{-1} (dry mass). In situ measurements of LCC are usually performed non-destructively via the Konica Minolta device Chlorophyll Meter SPAD-502Plus. The SPAD measures absorbance of LED-light by the leaf at two different wavelengths in the spectral domain of red and near-infrared. In the domain of red light, chlorophyll absorbs light strongly and in the near-infrared reflected light records differences in leaf structure. With these two values, a company defined SPAD-value is calculated by division of light transmission intensities.

Leaf carotenoid content

Plants contain a number of different types of carotenoids, which fall into the subgroups of carotenes or xanthophylls. Carotenoids are usually represented by two (α- and β-) carotenes and five xanthophylls (lutein, zeaxanthin, violaxanthin, antheraxanthin and neoxanthin) (Gitelson et al. 2003). 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 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 (µg cm^{-2}), or as mass per unit fresh leaf weight (mg g^{-1}).

Leaf anthocyanin content

Anthocyanins are the most common class of flavonoids, i.e., **the most widespread red pigments** (Hank et al., 2019). They include over 500 molecules and create a pink, red, purple or blue coloration in the tissue (the colours of autumn, Féret et al. 2017) depending on the molecule, temperature, and pH value. High content of Anthocyanins in plant leaves is an indicator of environmental stresses like intense sunlight, extreme temperature, drought or infections (Fassnacht et al. 2015).

Let's take a closer look at **pigments and their impact on reflectance spectra**. Note that chlorophyll and carotenoid content are not independent of each other. Usually, chlorophyll is about 4 to 5 times higher than the carotenoid content in green leaves. The Cab/Car ratio can be used as a stress indicator (see also Rock et al. 1988 and Hoque & Hutzler 1992):

- Higher **chlorophyll** a+b contents result in
  - lower green peak, the peak itself is shifted towards the left (blue).
  - „ red shift "of red edge (transition to NIR), i.e. inflection point moves to larger wavelengths
- Higher **carotenoid** contents result in
  - lower reflectance at 500-550 nm
  - Shift of green peak to larger wavelengths
- Higher **anthocyanin** contents result in lower reflectance at 530-580 nm

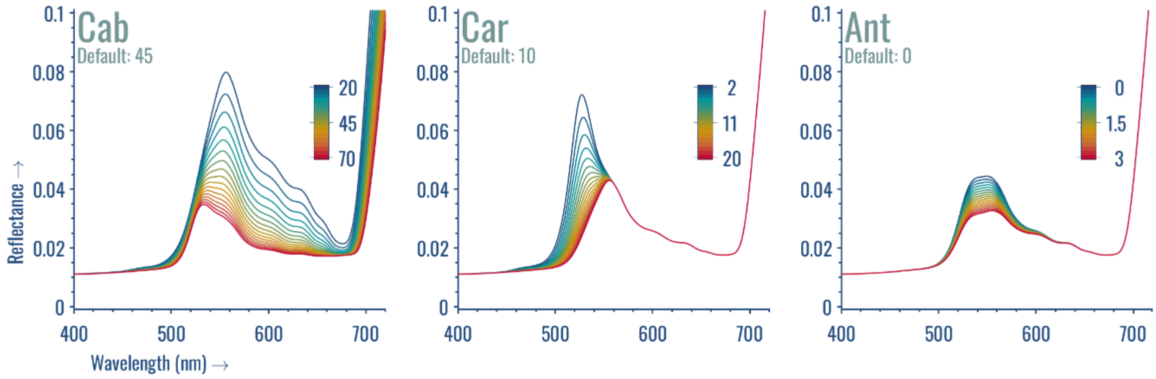


Figure 3.8 Changes in spectral reflectance in response to changes in pigment content (modelled with InFoRM, Buddenbaum & Hill 2020)

Leaf water content

Leaf water content describes the thickness of a theoretical layer of water (in cm), which absorbs radiation according to the Lambert–Beer law (Nobel, 2009). Hence, leaf water content 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}) is usually "observed" or retrieved (Clevers et al., 2010). "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).

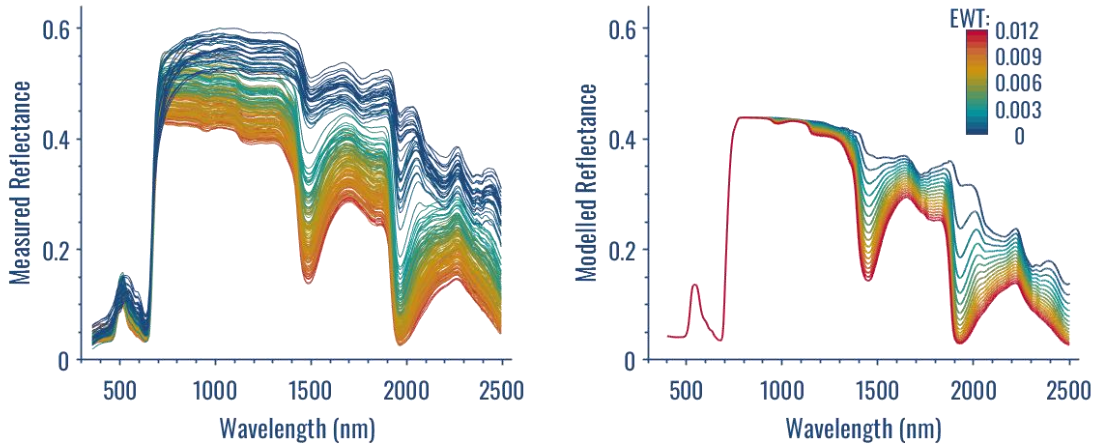


Figure 3.9 Measured spectra of oak leaves that were gradually dried (left) and PROSPECT-D model spectra where water content was varied in the same range of values (Buddenbaum & Hill 2020). The plots show that just changing the leaf water content in a reflectance model is not sufficient to capture the processes and structural changes in a drying leaf (EWT: equivalent water thickness)

Leaf thickness

Leaf thickness is a leaf structural variable that varies by species as well as by its position on the plant. It is determined by plant anatomy (including number, arrangement and size of leaf cells) and has been shown to affect photosynthesis. Leaf thickness is also positively correlated with leaf hydraulic conductivity, helping the plant to avoid water stress (Afzal et al. 2017).

Summary of leaf level variables

- *The inference of leaf level variables 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, …), which often are not considered in modeling approaches!*
- *The majority of methods estimating leaf level variables rely on parametric regressions, and some machine learning approaches (more information on retrieval approaches in the next lesson).*

Canopy level variables

Canopy level variables 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 multispectral data for the retrieval of canopy level variables is less obvious. Nonetheless, these variables are of **essential importance for forestry**.

Leaf Area Index (LAI)

The dimensionless leaf area index (LAI) characterizes plant canopies and is defined as green leaf area [m²] per unit ground area [m²]. 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 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.

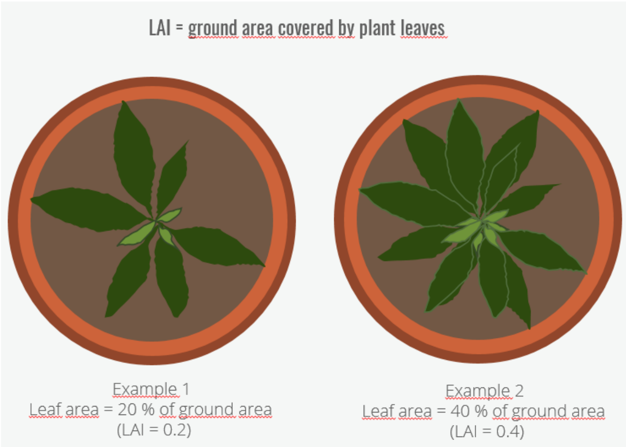


Figure 3.10 Examples of leaf area index

Leaf inclination angles

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 °).

In the leading canopy radiative transfer model SAIL the leaf inclination angles can either be described by the average leaf inclination angle (ALIA), or by a two-parameter function (leaf angle distribution function, LIDF). Typical distributions are called planophile, erectophile, plagiophile, extremophile, spherical, and uniform.

Vitality or Forest Health

“Numerous definitions of forest health exist, ranging from the recording of economic-related indicators to ecological-function indicators that preserve resilience and stability” (Lausch et al 2016). On the tree scale, health is often defined as the absence of disease or damage. Typical health indicators in forestry are parameters representing the health status of tree crowns as well as yield measures. Typical indicators that are usually recorded are crown thinning and yellowing. Lausch et al. (2016) name further examples including “the visible assessment of infestation levels, leaf defoliation, leaf chlorosis and other discolouration, dead branches, trunk damage, or the quantitative assessment of canopy damage or deterioration using metrics such as leaf area index, crown closure, numbers and volume of standing, dead and fallen trees.”

A number of these parameters are closely linked to the pigment composition, water and nutrient content, the photosynthetic activity as well as biomass of plants. As such, Imaging spectroscopy is well-suited for detecting and mapping stress in vegetation. For example, leaf water content affects the complete NIR/SWIR spectrum via the water absorption features at 980 and 1200 nm (weak absorption) and 1450, 1920, and 2600 nm (strong features) (Buddenbaum and Hill, 2020). Also, the leaf structure changes when leaves dry out. When acquiring hyperspectral images of a forest area, stress-relevant indicators are observed on canopy level. Thus, the general vitality or forest health can be estimated using the detailed spectral information of hyperspectral sensors (Asner et al., 2016, Lausch et al., 2016, Meiforth et al., 2020).

Productivity

The term productivity has been widely used in forestry-related literature with different definitions. In general, *primary productivity* is defined as the rate at which biomass is produced (i.e., energy produced by photosynthetic activity of green plants is stored). Li et al. (2020) describe the further division of primary productivity based on Odum (1959) “into *gross primary productivity*, the total rate of photosynthesis including the organic matter used up in respiration during the measurement period, and *net primary productivity* (NPP), the rate of storage of organic matter in plant tissues in excess of the respiratory utilization by the plants during the period of measurement”. These have become the standard definitions in ecological literature.

In a forest context, the term productivity is used to account for the accumulation of aboveground stem biomass, also referred to as yield, the item of interest to most foresters. The primary productivity in forested ecosystems is driven, in large part, by a suite of foliar structural and biochemical traits such as chlorophyll and nitrogen content that are visible to imaging spectrometers (Singh et al., 2015).

Tree Species

"Spatially explicit information on tree species composition of managed and natural forests is relevant for biomass or timber volume and quality estimation, habitat quality assessment, and biodiversity characterization. It thus provides valuable information for nature conservationists as well as for forest managers and is frequently required over large spatial extents" (Hill et al., 2019). Tree species composition is also an indicator of forest resilience, as mixed forest stands are more resilient to drought, forest fires or calamities.

Mapping tree species is one of the most common tasks in forest remote sensing and high spectral resolution "certainly has the potential to provide higher classification accuracies for forest species mapping than multispectral data" (Hill et al., 2019, Fassnacht et al., 2014, Sommer et al., 2016, Somers et al., 2013). Still, since all green vegetation has quite similar spectra, tree species classification is challenging. Thereby, multi-temporal data is beneficial for differentiating between tree species. However, frequent cloud cover in many regions of the world obscure the collection of observations from all required phenological stages (Stoffels et al. 2015). Often, additional information like structural information from secondary data sources such as LiDAR or Radar or texture information is included (Buddenbaum et al. 2005, Sommer et al. 2016).

Tree cover (trees per hectare) and crown size (diameter and height)

Forest inventories require the calculation of the number of trees per hectare and the basal area or woody biomass to assess the value of timber, while for forest monitoring, measuring changes in these variables is important for understanding ecosystem dynamics (Lechner et al. 2020). Such structural variables "depending on leaf arrangement and geometry, tree height or area, density, size, the shape of forest patches as well as fragmentation, complexity, and homogeneity are important characteristics of forests that strongly influence the spectral response of forest canopies" (Hill et al. 2019).

With high spatial resolution imagery, crown cover can be characterized by the extent of canopy cover versus ground cover (Lechner et al. 2020) and there is evidence that forest structure can be estimated based on texture (Hill et al. 2019). However, not with the accuracy and physical realism of active remote sensing systems. Of these, LiDAR is particularly good at characterizing (vertical) forest structure and can also directly measure tree height as well as individual crown shape and gap sizes by constructing 3D representations of forest structure (Lechner et al. 2020). Check out the FeMoPhys 3D crane site Aerial LiDAR Scan model of TUB in the next topic!

From leaf to canopy level variables

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

- Typically, LAI is used to upscale leaf-level variables to the canopy level (e.g. leaf chlorophyll content 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 homogeneous canopies. Usually, it is coupled with the PROSPECT model to "PROSAIL". There are extensions to account for forest structure like the models GeoSAIL and INFORM.

- 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).

Quiz: Variables of interest

What is the difference between leaf and canopy variables (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 traits below are described as canopy traits (multiple choice)

☐ Chlorophyll

☐ Leaf Area Index

☐ Leaf Water Content

☐ Tree species

What definition corresponds to the LAI? (single choice)

☐ The LAI characterizes plant canopies and is defined as green leaf area [m²] per unit ground area [m²]

☐ The LAI denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m² or g per cm² 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 acquisition

Campaign/Sampling design

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

Please be aware that these field measurements do not represent "the truth" which is why we prefer calling them ground references, ground measurements 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.

Join us for a very special field campaign!

You can probably imagine that it's hard to collect ground reference data from a forest canopy ... Variables that are frequently mapped are tree species and visual vitality parameters. In addition, LAI is a common variable that can be assessed from the ground by different means.

However, today, we are going to take you to a very special test site! The FeMoPhys project (2022 - 2027) aims to bridge the gap between remotely sensed data and the physiological and biochemical processes within trees. The project is being implemented at a research site in the Demmin area, North East Germany. It is also part of the TERENO long-term observatory and you might actually be familiar with the area if you participated in our soil MOOC.

Here, a 45 m rotating crane installed in the forest offers unique opportunities for research. The three-dimensional crown space of an old tree stand (including beech, oak, larch, Douglas fir and Norway spruce) is continuously accessible via the rotating crane jib. That way, an area of approximately one hectare is available for various measurements in the crown space of many tree individuals at different states of vitality. Okay, fair enough, this is absolutely not the standard of ground reference measurements in forestry. It's too good to miss—**take your chance to join us on a field trip** and, incidentally, gain insight into cutting-edge forest remote sensing research!

VIDEO: Forest-04: Imaging Spectroscopy for Forest Applications –

Field Measurements

URL of the video https://youtu.be/BvqJFYa2qrM

Well, that was a lot of field work! Still, some variables cannot be measured in-situ (in the field) but need to be assessed in the lab. Therefore, the leaf samples are quickly taken to Eberswalde and analysed for proteins, chlorophyll a and b, carotenoids, carbohydrates, starch, certain phenolic groups, and leaf water content, among others.

VIDEO: Forest-05: Imaging Spectroscopy for Forest Applications –

Laboratory methods

URL of the video https://youtu.be/2z5xk62luGU

As mentioned in the video, you can check out project details and a selection of recent results on specifically interesting tree individuals on the [FeMoPhys website](#)!

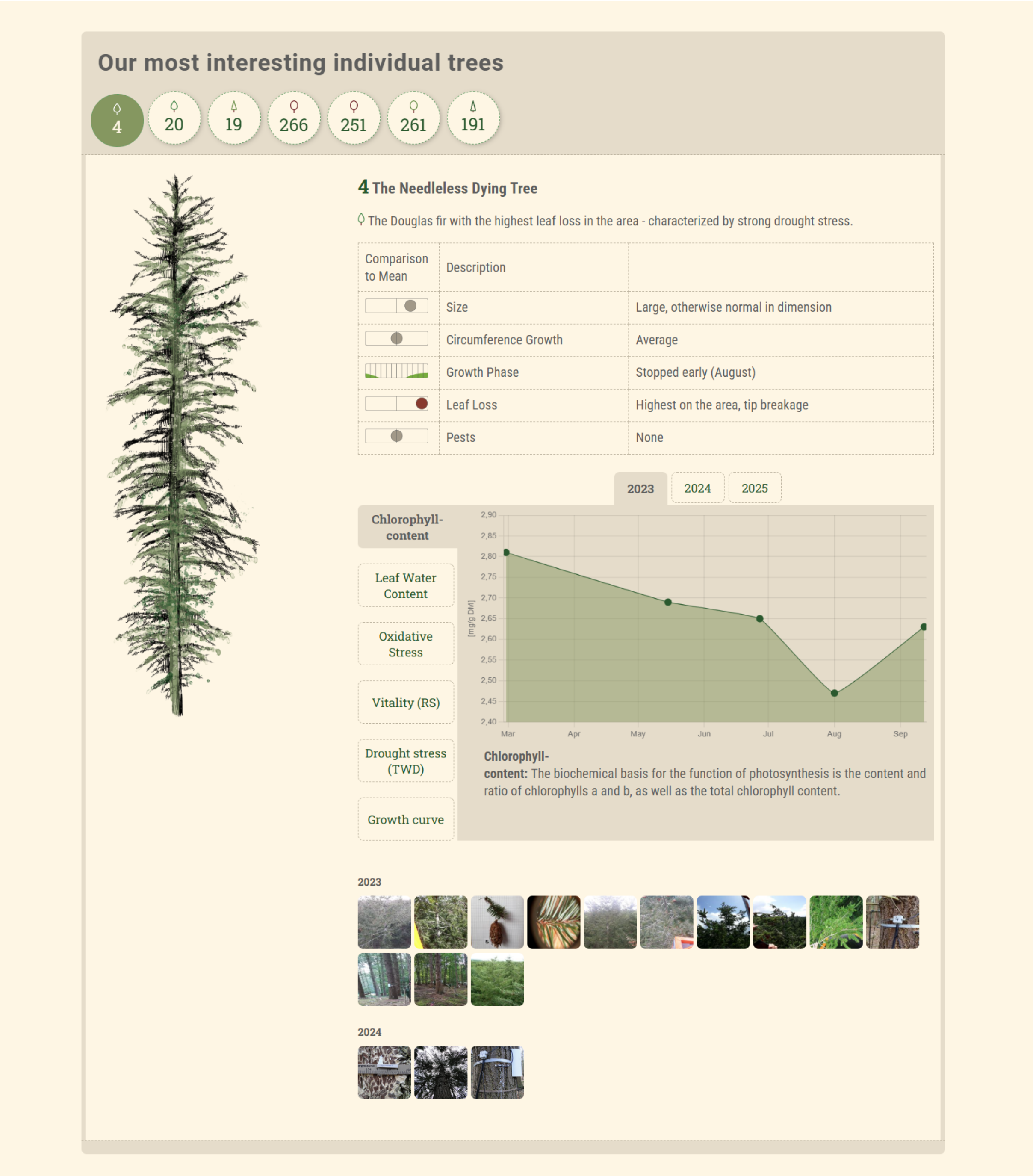


Figure 3.11 FeMoPhys website example

The close-up view of the forest canopy and the opportunity to do measurements in the crowns of mature trees really can change one's perspective ... as Micha and Fabian discuss here:

VIDEO: Forest-11.1: Expert interview: application field “forest”

URL of the video https://youtu.be/d0JHeCmcqNk

Quiz: Ground reference data acquisitions

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

- ☐ Chlorophyll a+ b
- ☐ Leaf area index (LAI)
- ☐ Leaf carotenoids content
- ☐ Leaf phenol and starch contents
- ☐ Leaf water content
- ☐ Tree species

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

3.4 Resources 'Imaging spectroscopy for forest applications'

In this section, we have assembled resources used for the creation of this lesson that we recommend for further reading as they provide a lot more detail. Please remember that this selection is not a complete overview of all resources – if you think an important resource is missing, let us and your fellow students know at hyperedu@eo-college.org.

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

How to cite: H. Buddenbaum, J. Hill (2020). **Imaging Spectroscopy of Forest Ecosystems - Exploiting the Potential of Hyperspectral Data**. HYPERedu, EnMAP education initiative, Trier University; originally published August 2020, revised February 2023.

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

Topic 1: Imaging spectroscopy of vegetation (for forest applications)

- Huete A.R. (2004). **Remote Sensing for Environmental Monitoring**. In: Artiola, J.F., Pepper, I.L, and M.L. Brussea (Eds), Environmental Monitoring and Characterization, Elsevier Academic Press, 183-206.
- Ustin S., Roberts D., Gamon J., Asner G., Green R. (2004). **Using imaging spectroscopy to study ecosystem processes and properties**, Bioscience, 54 (6), 523–534. https://doi.org/10.1641/0006-3568(2004)054[0523:UISTSE]2.0.CO;2
- Ustin, S.L., Jacquemoud, S. (2020). **How the Optical Properties of Leaves Modify the Absorption and Scattering of Energy and Enhance Leaf Functionality**, in: Cavender-Bares, J., Gamon, J.A., Townsend, P.A. (Eds.), Remote Sensing of Plant Biodiversity. Springer International Publishing, Cham, pp. 349-384.
- Gamon J.A., Somers B., Malenovský Z. et al. (2019). **Assessing Vegetation Function with Imaging Spectroscopy**. Surveys in Geophysics. 40, 489–513. https://doi.org/10.1007/s10712-019-09511-5

Topic 2: Variables of interest

- Afzal A., Duiker S.W. and J.E. Watson (2017). Leaf thickness to predict plant water status. Biosystems Engineering. Volume 156, April 2017, Pages 148-156. https://doi.org/10.1016/j.biosystemseng.2017.01.011
- Asner, G.P., Brodrick, P.G., Anderson, C.B., Vaughn, N., Knapp, D.E. & Martin, R.E. (2016). Progressive forest canopy water loss during the 2012–2015 California drought. Proceedings of the National Academy of Sciences, 113, E249-E255, http://doi.org/10.1073/pnas.1523397113
- Bréda N. (2003). Ground-based measurements of leaf area index: A review of methods, instruments and current controversies. Journal of Experimental Botany 54(392):2403-17. DOI:10.1093/jxb/erg263
- Buddenbaum, H., Schlerf, M. & Hill, J. (2005. Classification of coniferous tree species and age classes using hyperspectral data and geostatistical methods. International Journal of Remote Sensing, 26, 5453-5465, http://doi.org/10.1080/01431160500285076
- Clevers, J. (2010). Use spectral derivatives for estimating canopy water content. In W. Wagner, & B. Szekely (Eds.), 100 Years Isprs Advancing Remote Sensing Science, Pt 2 (pp. 143-147)
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Topic 3: Ground reference data acquisition

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3.5 Quiz: Introduction to imaging spectroscopy for forest applications

Please sort the traits below into canopy and leaf level traits

- ☐ Pigments
- ☐ Leaf Area Index
- ☐ Leaf Water Content
- ☐ Leaf inclination angle distribution (LAD)
- ☐ Tree species
- ☐ Tree cover and crown size
- ☐ Vitality or forest health

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

- ☐ Leaf chlorophyll content
- ☐ Leaf area index
- ☐ Leaf mass per area
- ☐ Tree Species

Which further influences can affect imaging spectroscopy data? (multiple choice)

- ☐ Soil
- ☐ Tree climbers fetching branches
- ☐ Undergrowth
- ☐ Illumination and viewing geometry

How can leaf level variables like chlorophyll content be measured in the in-situ in mature forests?

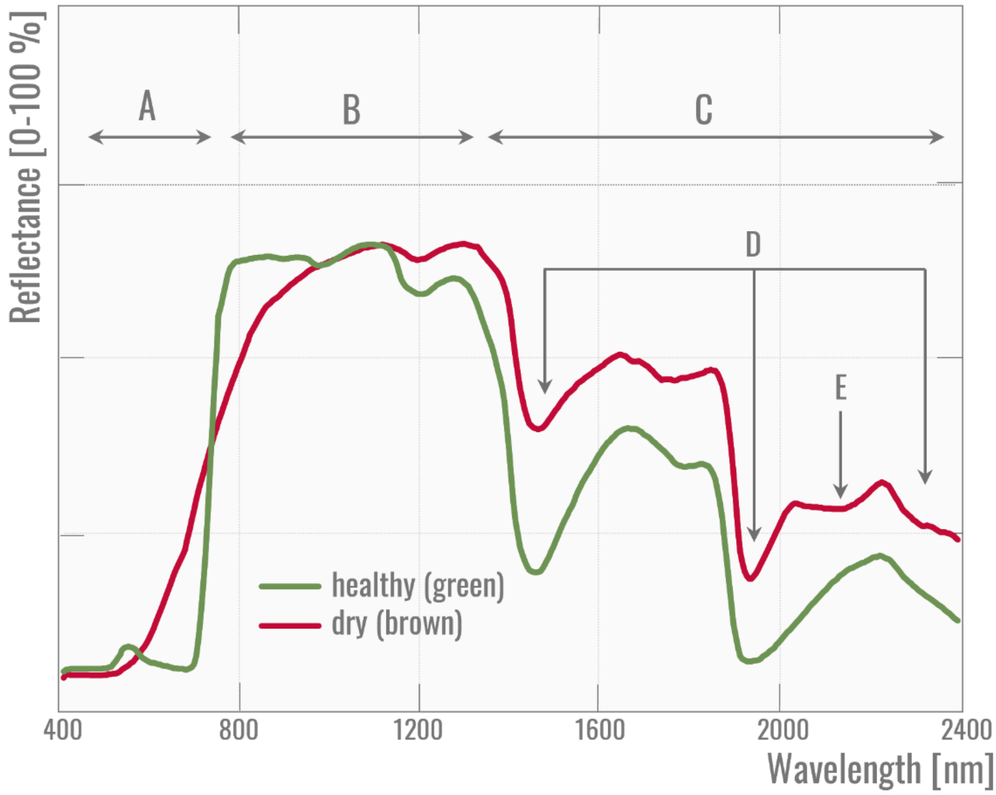
- ☐ Not at all
- ☐ By fetching branches e.g. with a crossbow
- ☐ By fetching branches e.g. by a tree climber
- ☐ By setting up a crane and collecting leaves from a gondola

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 …(see graph)

- ☐ Leaf pigments
- ☐ Cellulose
- ☐ Cell structure
- ☐ H_2O-absorption
- ☐ Water content



Spectra in courtesy of Hermann Kaufmann

Fill in the blanks

Potential answers to fill in the blanks:

- red/ green/ blue
- 550/ 800/ 2200 nm
- cellulose/ leaf pigments/ leaf mesophyll structure

The "Click or tap here to enter text. edge" is located around Click or tap here to enter text. nm and caused by the strong contrast in absorption of Click or tap here to enter text. and scattering by the Click or tap here to enter text..

What definition corresponds to the LAI? (single choice)

☐ The LAI characterizes plant canopies and is defined as green leaf area [m²] per unit ground area [m²]

☐ The LAI denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m² or g per cm² 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

What is the difference between leaf and canopy variables (multiple choice)

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

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

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

☐ In fact, there is not really a difference

Forest structural variables related to tree cover (trees per hectare) and crown size (diameter and height) can be estimated with highest accuracies using … (single choice)

☐ texture information in hyperspectral imagery

☐ Such information can only be assessed ground-based

☐ LiDAR is particularly good at characterizing (vertical) forest structure and can also directly measure tree height as well as individual crown shape and gap sizes by constructing 3D representations of forest structure

☐ multi-temporal data. However, frequent cloud cover in many regions of the world obscure the collection of observations from all required phenological stages

4. Methodological aspects

Welcome to this methodological lesson! Did you ever wonder during the previous 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 forest imaging spectroscopy. Then, we will provide more detailed information on the state-of-the-art techniques you will be trained in throughout this course. You'll also learn about data and software resources as well as the general workflow. As usual, what may sound dull, is actually a really fun lesson with lots of interactive content and videos! Skye will give you some more details on the learning objectives in the video below. Ready?

VIDEO: Forest-06: Imaging Spectroscopy for Forest Applications - Intro Lesson 2

URL of the video https://youtu.be/GngW8fx_GL4

4.1 Data and software resources

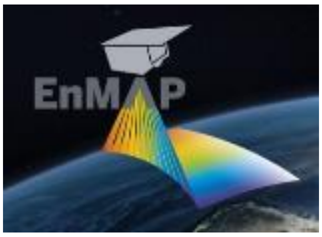
Data resources were quite a big topic in the basic MOOC 'Beyond the Visible: Introduction to Hyperspectral Remote Sensing'. In this topic, we've linked some of the resources that we think might be important if you are working in a forest context, including some updates and additional materials.

Data

For a long time, the availability of hyperspectral data was limited to expensive flight campaigns for small, selected areas with infrequent revisits (if at all). The "applications" were mostly related to scientific questions and method development rather than designed to answer real-world questions. Well, with the recent and upcoming launches of (additional) hyperspectral satellites, this is going to change!

Spaceborne:

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



EnMAP

EnMAP is the German hyperspectral observation satellite combining two hyperspectral sensors with more than 200 bands in the VNIR to SWIR range. EnMAP finally launched into space April 1st 2022 and data is becoming available for more and more regions of the world.

There are two main entry points to get EnMAP data using the Data Access Portal: the EnMAP Instrument Planning Portal and the EOWEB® GeoPortal. 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. Together with the EnMAP ground segment, we have produced four screencasts to guide you through the somewhat complicated process.

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 data 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 How to Perform A General Search discussing the basics of using EarthExplorer or an EarthExplorer Search Criteria discussing the available search options.

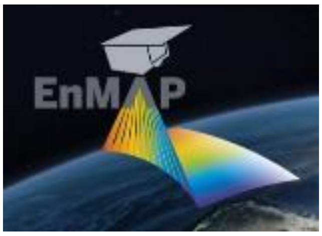
Airborne:

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

AVIRIS-NG Campaign Portal

AVIRIS-NG is an imaging spectrometer that measures reflected radiance at 5 nm intervals in the VNIR-SWIR spectral range from 380-2500 nm. The sensor has already been flown in several airborne campaigns in many countries. The AVIRIS-NG Data Portal provides an **overview of the campaign data and the possibility to download L1 and L2 data products.** In addition, reflectance data of the ESA CHIME & SBG AVIRIS-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 future 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 have been 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 made freely available to the scientific community under a Creative Commons License through the GFZ Data Services.

UAVs:

Unmanned aerial vehicles (UAVs) are increasingly used in forest applications due to their high spatial resolution and flexible deployment. They offer timely, repetitive data collection, addressing limitations of traditional remote sensing methods. Their adoption improves cost-efficiency, enhances monitoring precision, and supports informed forest management decisions.
Although most UAV data are generated by commercial providers, drones have still seen widespread use in forest monitoring due to their relatively low operational costs and ease of deployment for targeted data collection.

Headwall Nano HP Hyperspectral Imaging Package

The Nano HP is a compact VNIR hyperspectral imaging sensor **(400-1000nm)** with integrated GPS/IMU, designed for lightweight drones. It offers high-resolution data capture and fast, solid-state storage. Available as a turnkey system or payload, it supports DJI Enterprise and NDAA-compliant platforms like Harris Aerial and Freefly.

The Nano HP in action in Demmin (Image: Pixo)

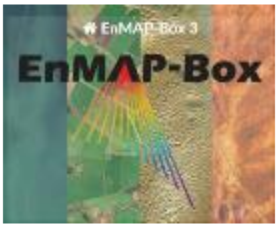
HySpex

The HySpex sensor consists of two separated push broom hyperspectral cameras, the HySpex VNIR-680 and the HySpex -SWIR 320m-e, which are manufactured by Norsk Elektro Optikk AS (NEO). The sensors have a spectral range of 400–2500 nm and a spectral sampling interval of 3.7 nm for VNIR (420–990 nm) and 6.0 nm for SWIR (970–2500 nm), resulting in a total of 408 spectral bands.

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 already and are certainly comfortable to use. Besides, the capabilities of **Geographic Information Systems (GIS)** such as e.g. 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. In addition, 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** such as that from the EnMAP mission, but also any other optical remote sensing data. The EnMAP-Box has been developed in the frame 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 forest applications **using the EnMAP Box in the next lesson**.

ARTMO

A software package for running and inverting a suite of RTMs such as the INFORM, is the **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

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

- ☐ EnMAP campaign portal
- ☐ AVIRIS portal
- ☐ ARES portal

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

- ☐ PRISMA
- ☐ EnMAP
- ☐ Hyperion
- ☐ SBG

If you want to visualize hyperspectral data, you can do so for 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
- ☐ Commercial imaging spectroscopy software such as ENVI

4.2 Methods

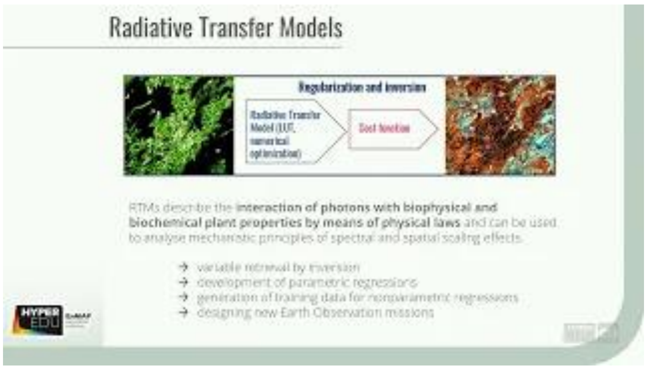
There are a **variety of methods for analyzing** the high information content of imaging spectroscopy data, depending on application and target variables. First of all, it is important that your data are properly preprocessed. And even if the data come at a high processing level, it might be helpful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

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

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

In the basic MOOC, we differentiated between **Classification and Quantification**. Now, we focus on **classification and quantification using linear and non-linear regression analysis and radiative transfer modelling (RTM).** In the following **video**, Skye gives you a general **overview of methods that are widely used in a forest imaging spectroscopy context.**

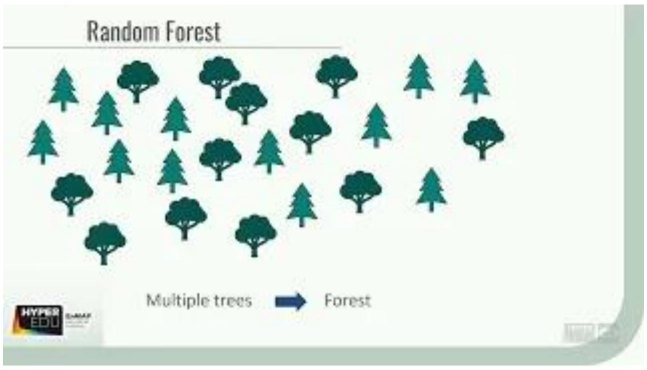
VIDEO: Forest-07: Imaging Spectroscopy for Forest Applications - General Methods



URL of the video https://youtu.be/OwLmvOtpjP0

In this course, we want to **focus on empirical classification methods that use machine learning algorithms and dimensionality reduction methods.** Therefore, in the following **video**, Skye will be a bit **more specific on** the definition of **"Empirical methods"**, what they include and which models are frequently used:

VIDEO: Forest-08: Imaging Spectroscopy for Forest Applications - Empirical Methods



URL of the video https://youtu.be/VUIsa1jS1-M

Quiz: Methods

Which classification method is best suited when tree species data are complex and overlapping? (single choice)

- ☐ Discriminant Analysis
- ☐ Principal Component Analysis
- ☐ Support Vector Machines
- ☐ Bootstrapping

Which of the following statements about Principal Component Analysis (PCA) are true? (multiple choice)

- ☐ PCA increases the number of bands in hyperspectral data.
- ☐ PCA creates uncorrelated components ranked by the variance they explain.
- ☐ PCA preserves a direct connection to the original spectral wavelengths.
- ☐ PCA helps reduce dataset size while keeping most relevant information.

Fill in the blanks:

In Support Vector Machines, a boundary called a **Click or tap here to enter text.** (decision tree/hyperplane) is used to separate different classes of data points. The algorithm chooses the boundary that maximizes the **Click or tap here to enter text.** (variance/margin) between the classes. The data points that lie closest to this boundary, and are critical in defining it, are called **Click or tap here to enter text.**(support vectors /spectral indices).

What does the 'random' in Random Forest refer to?

- ☐ Random noise added to the labels
- ☐ Random selection of training data for deep learning
- ☐ Random sampling of both data and features during training

☐ Random pruning of decision trees after training

True or False

True or False: Deep learning models like CNNs require only a small number of labeled samples to train effectively. **Click or tap here to enter text.**

Which of the following best describes how Random Forest improves model robustness?

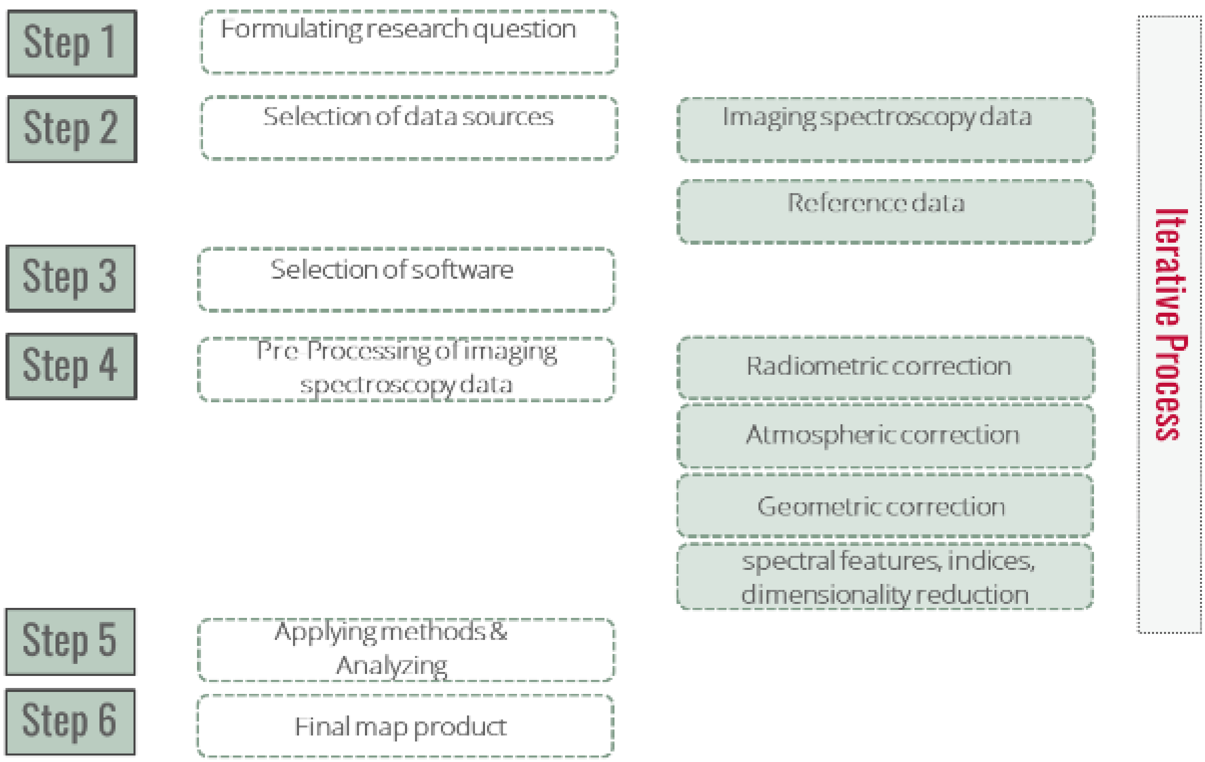
☐ It prunes each tree to reduce overfitting
☐ It applies a kernel trick to non-linear data
☐ It uses multiple decision trees trained on bootstrapped and randomly sampled features
☐ It transforms spectral data into components using PCA

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 might seem familiar. If so, you would be right - it is! And you might have solved it before ... You see, we think it is important to become familiar with forest applications in the context of an entire workflow, including the final map product, preprocessing, choice of software, data acquisition etc. Have a guess and **place** the six different steps involved including some more concrete sub-steps (Step 2 and Step 4) **in the correct order**!

You are almost ready to get started with your analyses! However, before you get your hands dirty, think about what to consider in your workflow.



Of course, the workflow shown is abstract and simplified and you might experience situations where you must iteratively go back and adjust. Nevertheless, the exercise shows that the path to a final, qualitative (or even quantitative) map product based on imaging spectroscopy data involves many steps whose precise definition requires intensive thought and consideration.

Quiz: Workflow

What is the correct sequence in the workflow for retrieving forest traits from hyperspectral data?

☐ Classification → Dimensionality Reduction → Pre-processing → Validation

☐ Pre-processing → Feature Selection → Classification → Validation → Interpretation

☐ Validation → Classification → Feature Selection → Pre-processing

☐ Interpretation → Classification → Pre-processing → Validation

Which preprocessing steps should be applied to hyperspectral data in general? (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 Sources and further reading

In this section, we have assembled resources used for the creation of this lesson that we recommend you 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 know at hyperedu@eo-college.org.

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

How to cite: H. Buddenbaum, J. Hill (2020). **Imaging Spectroscopy of Forest Ecosystems - Exploiting the Potential of Hyperspectral Data**. HYPERedu, EnMAP education initiative, Trier University; originally published August 2020, revised February 2023.

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

Topic 1: Data and software resources

EnMAP Data

- www.enmap.org
- https://eoweb.dlr.de
- Guanter, L., Kaufmann, H., Segl, K., Foerster, S., Rogass, C., Chabrillat, S., Kuester, T., Hollstein, A., Rossner, G., Chlebek, C., Straif, C., Fischer, S., Schrader, S., Storch, T., Heiden, U., Mueller, A., Bachmann, M., Mühle, H., Müller, R., Habermeyer, M., Ohndorf, A., Hill, J., Buddenbaum, H., Hostert, P., Van der Linden, S., Leitão, P.J., Rabe, A., Doerffer, R., Krasemann, H., Xi, H., Mauser, W., Hank, T., Locherer, M., Rast, M., Staenz, K. & Sang, B. (2015) The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation. Remote Sens. 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://youtu.be/VoBGJjMZoNY?si=QULtPjU9E93uS_7k
- 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/

4.5 Quiz: Methodological aspects

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

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

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

- ☐ Average
- ☐ Airborne
- ☐ Advanced
- ☐ Avenger

Remember? If you want to visualize 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

Why is geometric correction important? (multiple choice)

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

Which of the following is not a subgroup of forest variables mentioned in the lecture?

- ☐ Biochemical variables
- ☐ Biological variables
- ☐ Climatic variables
- ☐ Geometrical variables

What are important considerations before choosing a model for forest trait retrieval?

- ☐ Interpretability
- ☐ Planetary alignment
- ☐ Accuracy
- ☐ Scalability
- ☐ Processing time

Which of the following methods fall under empirical models?

- ☐ Support Vector Machines
- ☐ Radiative Transfer Models
- ☐ Partial Least Squares Regression (PLSR)
- ☐ NDVI
- ☐ Principal Component Analysis

What is a major advantage of Random Forest over a single decision tree?

- ☐ It always achieves perfect accuracy
- ☐ It uses fewer training samples
- ☐ It aggregates results from many trees trained on random subsets
- ☐ It does not require bootstrapping

Which regression method is known for handling high-dimensional predictor variables well with relatively small training samples?

- ☐ NDVI
- ☐ Linear Regression
- ☐ Partial Least Squares Regression (PLSR)
- ☐ Support Vector Machine

Which of the following best describes a *hybrid method* in the context of forest trait retrieval?

- ☐ A method that only uses field-based ground truth data
- ☐ A combination of radiative transfer models and machine learning
- ☐ A simplified version of a physical model
- ☐ A traditional index-based approach

5. 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 results we strongly encourage you to use this opportunity to "get your hands dirty" during some expert-guided hands-on training exercises! As before, Skye will explain the learning objectives of this – final – lesson in the video below.

VIDEO: Forest-09: Imaging Spectroscopy for Forest Applications - Lesson 3 Intro

URL of the video https://youtu.be/Y7xKT8I5cAM

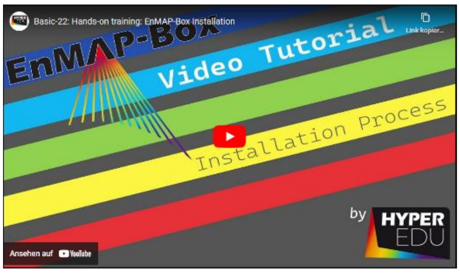
Let's move on with the first topic of this lesson!

5.1 Introduction to the EnMAP-Box

As Skye just explained, we will be using a classification workflow within the EnMAP Box applications to learn how to retrieve a tree species map 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 explains 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

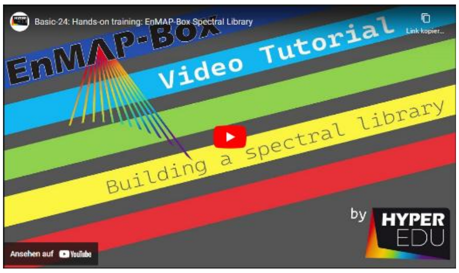
Video: Basic-22: Hands-on training: EnMAP-Box Installation



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: Tree species classification

Okay, here we go. In the following screencasts, we will guide you step by step through the process of working with hyperspectral data of forest areas. You will begin by exploring and becoming familiar with a hyperspectral image containing a forested area and the spectral information contained in it. Next, we will demonstrate how to generate tree species classification maps using dimensionality reduction techniques and different classification algorithms. Finally, we will show you how to validate your results.

For active participation, you can download the data here.

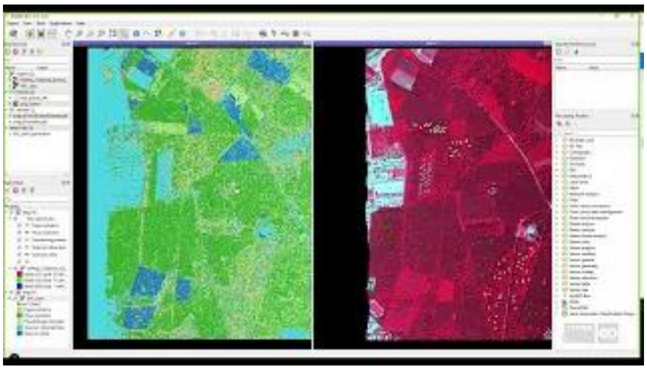
Get acquainted with the data

VIDEO: Forest-10.1: Tutorial - Data

URL of the video https://youtu.be/0kRoGj4HjgQ

Produce a tree species map. How to use dimensionality reduction, retrieve classification results and lastly, how to validate your results

VIDEO: Forest-10.2: Tutorial - Classification algorithms



URL of the video https://youtu.be/mT0tk93bIpA

You might find that your results differ from ours. Don't worry, that's normal ☺. As the number of our reference field samples is limited, we use cross-validation for training the algorithm as well as for validation of our results. This means that our 250 training data points are split into groups – in our case, ten groups with 25 samples each - of which nine are used for training and one for validation. The algorithm will assign different samples to the groups in each run, meaning that the training as well as the validation database slightly differ each run. Thus, the results of each classification will slightly differ as well.

Quiz: EnMAP-Box Tree species classification

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

- ☐ AVIRIS-NG
- ☐ EnMAP
- ☐ PRISMA
- ☐ HyMap

What is the function of the 'aggregate spectral profiles' tool in EnMAP Box? (single choice)

- ☐ Merge vector layers
- ☐ Combine training samples
- ☐ Create mean spectra per species
- ☐ Apply classification rules

What are the main roles of the EnMAP Box in this workflow? *(multiple choice)*

- ☐ Visualization of hyperspectral images
- ☐ Training of machine learning classifiers
- ☐ Capturing in-situ data
- ☐ Performing spectral analysis

5.3 Discussion of accuracy and limitations

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

There are several important considerations when comparing ground-based and remote sensing data in forest environments. Firstly, our field reference data isn't entirely "ground truth" because many forest variables—such as leaf pigment content, moisture levels, or structural traits—can vary greatly across both space and time. Additionally, due to practical constraints, we only collected a limited number of samples.

Another major challenge lies in the mismatch between spatial scales: field measurements are taken at very small, often leaf-level scales, while airborne or satellite sensors observe much larger areas, often capturing the entire forest canopy as a single, integrated signal. This scale discrepancy introduces a level of uncertainty that is frequently overlooked in remote sensing validation studies.

For instance, in forest ecosystems, chemical composition of leaves with respect to chlorophyll, nitrogen, or water content can vary not only between different plant organs (leaves, branches, trunks) but also vertically. Processes like leaf ageing or senescence often begin in the lower canopy and progress upward. Unfortunately, many field instruments (e.g., the SPAD leaf-clip chlorophyll meter) are only practical for sampling individual leaves in accessible parts of the canopy and cannot capture this full vertical or spatial variability.

On the other hand, hyperspectral sensors mounted on aircrafts or satellites observe the canopy from above and aggregate reflectance signals across multiple canopy layers, without distinguishing between leaves, branches, or other components. This integration, also shaped by the sensor's point spread function, makes it difficult to directly compare remote sensing data to field measurements made at specific heights or on specific plant parts. As a result, discrepancies between ground and remote observations are common—and to be expected—due to these fundamental differences in measurement scale and scope.

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 deviations between the retrieved products (e.g., species classification maps) and "hypothetically true" values obtained from in situ measurements during ground campaigns (the tree species that grows at the specific location and forms the main canopy). This approach is relatively straightforward because it directly compares the remote sensing results with known field data. In addition to class assignments, one can explore the probability of a pixel to be assigned to a certain class.

For tree species classification or other forest-related applications, supervised classification techniques are often employed, where a model is trained using labeled examples, such as forest types identified in field plots, to classify remote sensing images. Common algorithms for this purpose include Random Forest (RF), Support Vector Machines (SVM), and Neural Networks (NN). One of the standard tools for evaluating classification accuracy is the confusion matrix, also known as the error matrix. This matrix compares the predicted classifications from remote sensing data with the actual classes derived from reference data. From this matrix, several important accuracy metrics are calculated. Overall accuracy measures the percentage of correctly classified samples, while user's accuracy indicates the likelihood that a pixel labeled as a particular class truly belongs to that class. Producer's accuracy reflects the likelihood that a reference sample from a given class was correctly identified in the classification. Additionally, the Kappa coefficient is used to assess the agreement between the classification and reference data while accounting for the possibility of agreement occurring by chance. To further evaluate the performance of these classification models, the F1 score is commonly used. The F1 score is the harmonic mean of precision and recall, providing a single metric that balances how many of the predicted positives are truly positive (precision) and how many of the actual positives are correctly identified (recall). This comprehensive approach allows for a thorough evaluation of classification accuracy and model performance in remote sensing studies.

Quite a number of hyperspectral forestry applications are still being developed and are not quite operational yet. There are loads of experiences and even experts don't always share the same opinion … To conclude this course and get a glimpse of where the hyperspectral forestry journey might lead, join Micha and Fabian for a discussion on current issues in imaging spectroscopy of forests:

VIDEO: Forest-11.3: Expert interview: application field “forest”

URL of the video https://youtu.be/wrFJplFtYL4

VIDEO: Forest-11.4: Expert interview: application field “forest”

URL of the video https://youtu.be/bJRFuImz2e8

Quiz: Accuracy and limitations

Why is it challenging to directly compare hyperspectral remote sensing data with ground-based measurements in forest environments? (single choice)

- ☐ hyperspectral sensors cannot detect pigments such as chlorophyll or nitrogen
- ☐ field instruments are more accurate than hyperspectral sensors and always reflect true canopy values.
- ☐ there is a mismatch in spatial scale and measurement depth between remote sensing and field methods. (CORRECT)
- ☐ trees are just really good at hiding their secrets from satellites

What does the confusion matrix measure? (Single choice)

- ☐ Image resolution
- ☐ Classification accuracy (CORRECT)
- ☐ GPS error
- ☐ Data storage efficiency

In classification accuracy assessment, what does producer's accuracy refer to? (Single choice)

- ☐ The probability a pixel belongs to the labelled class
- ☐ How many samples were collected
- ☐ The likelihood a reference sample is correctly classified (CORRECT)
- ☐ Agreement due to chance

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 know at hyperedu@eo-college.org.

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

How to cite: H. Buddenbaum, J. Hill (2020). **Imaging Spectroscopy of Forest Ecosystems - Exploiting the Potential of Hyperspectral Data**. HYPERedu, EnMAP education initiative, Trier University; originally published August 2020, revised February 2023.

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

Topic 1: Introduction to the EnMAP-Box

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

Topic 2: EnMAP-Box Tree species classification

- Alternative tutorial using the same data on “Tree classification” by Fabian Fassnacht in R: https://github.com/fabianfassnacht/treespeciesclassification/blob/main/README.md

Topic 3: Discussion of accuracy and limitations

- Banko, G. (1998) A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data and of Methods Including Remote Sensing Data in Forest Inventory. IIASA Interim Report . IIASA, Laxenburg, Austria, IR-98-081 Copyright © 1998 by the author(s). http://pure.iiasa.ac.at/5570/

- Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., ... & Ghosh, A. (2016). Review of studies on tree species classification from remotely

sensed data. Remote sensing of environment, 186, 64-87, https://doi.org/10.1016/j.rse.2016.08.013

- Fassnacht, F. E., White, J., Wulder, M., Næsset, E., **Remote sensing in forestry: current challenges, considerations and directions**, *Forestry: An International Journal of Forest Research*, Volume 97, Issue 1, January 2024, Pages 11–37, https://doi.org/10.1093/forestry/cpad024
- 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.
- Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). **Good practices for estimating area and assessing accuracy of land change.** Remote sensing of Environment, 148, 42-57.
- Olofsson, P., Stehman, S. V., Woodcock, C. E., Sulla-Menashe, D., Sibley, A. M., Newell, J. D., ... & Herold, M. (2012). **A global land-cover validation data set, part I: Fundamental design principles.** International Journal of Remote Sensing, 33(18), 5768-5788.
- 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.

5.5 Quiz: Hands-On Training

What is a major reason for discrepancies between remote sensing and field data in forest studies? *(single choice)*

- ☐ Satellites are less reliable
- ☐ Leaf measurements are always inaccurate
- ☐ Difference in spatial scale between field and remote sensing data
- ☐ Trees do not reflect light consistently

Which variable is typically *not* directly observable from hyperspectral sensors? *(multiple choice)*

- ☐ Chlorophyll concentration
- ☐ Tree height
- ☐ Crown cover
- ☐ Leaf-level nitrogen content

What do spectral residuals help to quantify? *(single choice)*

- ☐ Reflectance intensity
- ☐ Tree density
- ☐ Difference between observed and predicted spectral values
- ☐ Number of spectral bands

Why do coniferous species appear darker than broadleaved species in near-infrared bands? *(single choice)*

- ☐ They reflect more green light
- ☐ They reflect less in the near-infrared
- ☐ They are smaller
- ☐ They are denser

Which of the following are sources of uncertainty when comparing in-situ and remote sensing data in forests? *(multiple choice)*

- ☐ Temporal variability of vegetation
- ☐ Spatial resolution mismatch
- ☐ Sensor calibration errors
- ☐ Availability of internet connection

What can affect the comparison between leaf-level field measurements and canopy-level hyperspectral data? *(multiple choice)*

- ☐ Vertical gradients in biochemical properties
- ☐ Differences in viewing geometry
- ☐ Leaf reflectance always increases with height
- ☐ Coarse spatial resolution of remote sensors

Which of these are common forest traits targeted in remote sensing studies? *(multiple choice)*

- ☐ Tree height
- ☐ Leaf Area Index (LAI)
- ☐ Soil salinity
- ☐ Crown cover

In the classification accuracy report, which of the following can be derived from the confusion matrix? *(multiple choice)*

- ☐ User's accuracy
- ☐ Precision
- ☐ Bandwidth usage
- ☐ Producer's accuracy

Which types of remote sensing data are suitable for tree species classification? *(multiple choice)*

- ☐ Hyperspectral data
- ☐ RGB drone imagery
- ☐ Multispectral data
- ☐ LiDAR (when combined with spectral data)

In the EnMAP Box, what tasks can be performed using the spectral library tool? *(multiple choice)*

- ☐ View spectral profiles of clicked pixels
- ☐ Extract mean spectra per species
- ☐ Apply raster classification directly
- ☐ Assign colors based on species

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 via email at eo-college

6.2 Final Exam

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

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

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

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

- ☐ … becomes increasingly flat (less pronounced absorption features)
- ☐ … becomes increasingly more similar to a soil spectrum
- ☐ … remains the same except for changes in the VIS region

Which classification method is best suited when tree species data are complex and overlapping? (single choice)

- ☐ Discriminant Analysis
- ☐ Principal Component Analysis
- ☐ Support Vector Machines
- ☐ Bootstrapping

What does the 'random' in Random Forest refer to? (single choice)

- ☐ Random noise added to the labels
- ☐ Random selection of training data for deep learning
- ☐ Random sampling of both data and features during training
- ☐ Random pruning of decision trees after training

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 important considerations before choosing a model for forest trait retrieval? (multiple choice)

☐ Interpretability

☐ Planetary alignment

☐ Accuracy

☐ Scalability

☐ Processing time

What are the main roles of the EnMAP Box in this workflow? (multiple choice)

☐ Visualization of hyperspectral images

☐ Training of machine learning classifiers

☐ Capturing in-situ data

☐ Performing spectral analysis

Why do coniferous species appear darker than broadleaved species in near-infrared bands? (single choice)

☐ They reflect more green light

☐ They reflect less in the near-infrared

☐ They are smaller

☐ They are denser

What can affect the comparison between leaf-level field measurements and canopy-level hyperspectral data? (multiple choice)

- ☐ Vertical gradients in biochemical properties
- ☐ Differences in viewing geometry
- ☐ Leaf reflectance always increases with height
- ☐ Coarse spatial resolution of remote sensors

What is a major advantage of hybrid models in forest trait retrieval?

- ☐ They guarantee 100% accuracy and come with a free forest.
- ☐ They combine the scalability of machine learning with the physical basis of RTMs.
- ☐ They use artificial intelligence to predict the next tree species evolution.
- ☐ They replace the need for satellites entirely.

Match the model or method (left) with its correct category (right).

1. Random Forest	1. non-Parametric Regression
2. PLSR	2. Empirical Parametric Regression
3. PROSPECT	3. Leaf-level RTM
4. NDVI	4. Machine Learning
5. DART	5.Canopy-level RTM

Drag each trait into the category it belongs to

<u>Trait Categories (Target Boxes):</u>

1. Biophysical Traits
2. Biochemical Traits
3. Biological Traits
4. Geometrical Traits

<u>Traits:</u>

- Leaf area index
- Forest phenology
- Leaf chlorophyll content
- Canopy structure

- Biomass
- Leaf nitrogen content
- Average leaf inclination angle
- Leaf water content
- Forest canopy temperature

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

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

Which further influences can affect imaging spectroscopy data? (multiple choice)

☐ Soil

☐ Tree climbers fetching branches

☐ Undergrowth

☐ Illumination and viewing geometry

Which of the following are examples of parametric regression indices commonly used in forest trait retrieval? (multiple choice)

☐ NDVI

☐ PRI

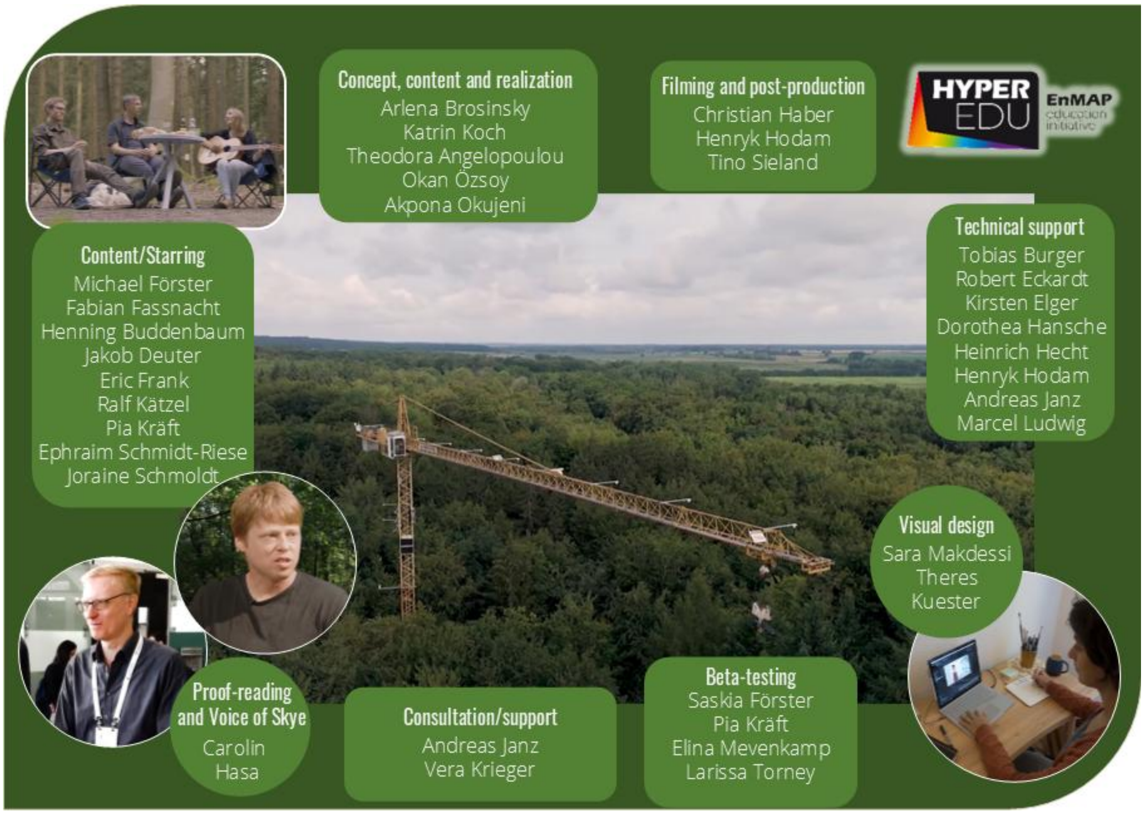
☐ PLSR

☐ Random Forest

☐ NDI

6.3 Goodbye!

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



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.