

E-TRAINEE: OPEN E-LEARNING COURSE ON TIME SERIES ANALYSIS IN REMOTE SENSING

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ABSTRACT:

Time series (TS) analysis has always been an important topic in Remote Sensing (RS). Open access to archives of Earth Observation missions, periodically acquired nation-wide aerial imagery and LiDAR point clouds, and various research datasets, together with open tools for TS data processing, have brought new possibilities in RS research but also challenges in education. The topic of TS analysis in RS has become an essential part of MSc curricula in geoinformatics, geography, and related fields. Open learning materials systematically addressing the issue of TS at the master's level are rare and their development is time and resource demanding. Thus, based on previous collaboration, the four research groups from Charles University, Heidelberg University, University of Innsbruck, and University of Warsaw joint their specific expertise and developed an open E-learning course on Time Series Analysis in RS for Understanding Human-Environment Interactions (E-TRAINEE). The course consists of four Modules covering the topics of TS from general approaches (M1) to specific methods of processing TS of satellite multispectral images (M2), 3D/4D point clouds (M3), and aerial image and laboratory spectroscopy (M4). Theoretical parts are supported with exercises/tutorials and case studies based on research activities of the involved teams. The course is accessible via a web site and is published under the CC-BY SA 4.0 license. The primary target group are MSc and PhD students of geoinformatics and geography, but it is also relevant to students of environmental studies, ecology, or geology, as well as potential users from the public and private sectors dealing with applications of RS.

1. INTRODUCTION

Time series (TS) analysis is a frequent and challenging topic of both today and future research in remote sensing (RS). Global Earth observation (EO) programmes provide extensive image archives dating back several years or even decades (e.g., Sentinel, Landsat). On a country-wide scale, aerial images, LiDAR and photogrammetric point clouds are acquired in two- to three-year cycles. With an increasingly supported and accepted open data policy, free access to these data sources has become a well-recognised practice. Specific sites are monitored on a regular basis (weekly, monthly, yearly) for diverse research purposes, e.g., applications connected to ecology and environmental studies, such as resistance of plants to drought, invasive species encroachment, decrease of biodiversity, deforestation, melting of mountainous glaciers, or desertification. Processing of TS of RS data demands knowledge of handling large datasets (big data) and advanced statistical methods, including machine and deep learning (e.g., Sudmanns et al., 2019). Nowadays, solutions offering access to open archives of satellite images and cloud processing exist (e.g., Google Earth Engine, GEE). To benefit from such services and be able to report on the achieved quality of the results, a user must have a deep knowledge about the used

data and applied processing methods. On the other hand, these services are not suited for data from different sources than specific sensor(s) (such as Landsat or Sentinel). Thus, processing and analysis of the TS at different time and spatial scales, the combination of heterogeneous and multi-modal data sources, and quality assessment of the results have necessarily become key parts of RS and/or geoinformatics curricula.

In 2019, TS processing workflows were not so well established in the university study programs. A comprehensive course that would increase students' methodological background and digital literacy in remote sensing time series (RSTS) analysis and at the same time develop their skills for communication of complex data processing tasks, enabling them for interdisciplinary research missions in the future, was missing. Thus, initially supported by the institutional collaboration within the 4EU+ University Alliance (4EU+, 2023), an international team consisting of four research groups in the fields of geoinformatics and RS was established and started to develop learning materials examining RSTS from various perspectives. Joining the specific expertise and knowledge of the research groups from Charles University, Heidelberg University, University of Innsbruck, and

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University of Warsaw resulted in an open E-learning course on Time Series Analysis in RS for Understanding Human-Environment Interactions (E-TRAINEE).

The primary target group of the course are MSc and PhD students of geoinformatics and related geographical fields who specialize in RS for monitoring Earth surface dynamics and changes. But it is also relevant to students of environmental studies, ecology, or geology dealing with applications of RS and potential users from the public and private sectors, such as practitioners of national environmental and conservation agencies, research institutes, or companies offering services in RS.

During the three years of the course development (2020/09/01 – 2023/08/31) a number of learning and training materials on RS data analysis have been published online (e.g., EO4GEO, 2023, EOL Humboldt University, 2023). Nevertheless, none of them deals with the topic of RSTS analysis in such level of detail, variety of practical examples, hands-on exercises, and applications.

2. COURSE STRUCTURE AND CONTENT

The E-TRAINEE course consists of four Modules. The first one provides a general overview of methods for RSTS analysis. The other three Modules focus on specific processing steps and analyses connected to different types of data (Figure 1). After completing Module 1, the design of the course enables the students to concentrate either on one or more selected learning modules in any order. Some of the theory in Modules 2 – 4 is related to Module 1, and it is linked accordingly.


 E-learning course on Time Series Analysis in Remote Sensing for Understanding Human-Environment Interactions	
Prerequisites	
Module 1 Methods of Time Series Analysis in Remote Sensing	Module 2 Satellite Multispectral Images Time Series Analysis
	Module 3 3D/4D Geographic Point Cloud Time Series Analysis
	Module 4 Aerial Image and Laboratory Spectroscopy Time Series Analysis
	Software
Use Cases and Data	

Figure 1. The course structure.

Each “Module” contains several “Themes” divided into a theoretical section and exercises/tutorials. The theoretical parts are supported with a list of references and literature for further reading, and they are concluded with self-evaluation quizzes. The quizzes are arranged in such a way that the first couple of questions check whether the students read and understood the theoretical part; the subsequent questions show if they are able to apply the acquired knowledge. In general, each exercise/tutorial consists of a description of its objectives, used datasets and software packages, guidance through the exercise, and a list of tasks. In addition to that, it includes an example solution that can be used as an alternative form of self-evaluation. As the course material is rather rich, especially regarding the practical parts, it is indicated which of the exercises are compulsory and which are

optional. Moreover, Modules 2 – 4 include two or three “Case Studies” with a deeper look into selected research problems. They are practically oriented and give the participants an opportunity to solve a more complex practical task than in the case of exercises/tutorials. The practical exercises are based on open software tools such as QGIS, CloudCompare, EnMAP-Box, Google Earth Engine, or scripting in Python or R. A special section of the course is dedicated to the list of used software including installation instructions and tutorials (Figure 1).

The course section entitled “Prerequisites” summarises basic knowledge in RS, statistics, and programming that is required to follow the course; links to available external online learning materials are provided.

The methods, datasets and case studies presented in Modules 1 – 4 are on various levels connected to past or ongoing research projects of the involved institutions and are related to the applications of RS in environmental studies (see Sections 2.1 – 2.4 for details). The datasets used are either existing open archives (e.g., Copernicus, Landsat programmes) or they were collected within the research projects (e.g., LiDAR point clouds, Remotely Piloted Aircraft Systems (RPAS) hyperspectral images, laboratory and in-situ spectroradiometer measurements) and are released, as well as other course materials, under a Creative Commons (CC BY) license. A description of the use case datasets is available in an additional course section (Figure 1).

2.1 Module 1: Methods of Time Series Analysis in RS

Module 1 (M1) of the E-TRAINEE course covers general principles and methods that are applicable to the analysis of RSTS from different platforms and sensors. In addition to explaining theoretical concepts, the module provides practical tutorials and exercises which are based on the general-purpose programming language Python and selected libraries for geospatial applications, domain-specific analytics, and visualization, complemented by QGIS with its graphical user interface for certain tasks. While most of the hands-on parts in M1 exemplarily use optical satellite imagery, many of the approaches introduced here are transferrable to other data types (such as TS of close-range images or 3D point clouds from laser scanning). The module is structured into the following six Themes (T):

- M1.T1 Principles of remote sensing time series
- M1.T2 Large time series datasets in remote sensing
- M1.T3 Time series analysis based on classification
- M1.T4 Trajectory-based analysis
- M1.T5 Spatio-temporal data fusion
- M1.T6 Reference data, validation and accuracy assessment

The first Theme (M1.T1) aims to convey a fundamental understanding of RSTS. First, it introduces important principles and concepts of TS in general (not RS specific) and illustrates how to look at typical properties of TS. Second, it summarizes the principles of RS, as a prerequisite to understanding how RSTS are acquired and what needs to be considered when using them. Based on this, the key principles of RSTS are introduced next, including their typical contents and structure as well as the concepts of extent, resolution, and scale in different domains (spatial, spectral, radiometric, and temporal). These aspects are briefly discussed in relation to the observed phenomena, and some general preprocessing considerations (such as quality control, gap filling, resampling, smoothing) are outlined. An interactive tutorial, implemented as a Python Jupyter Notebook, guides students through the first steps with Python’s xarray

package (Hoyer and Hamman, 2017) for handling and processing a sample TS of Sentinel-2 satellite imagery. Subsequent Themes largely build on the skills obtained in this tutorial for handling RSTS as labelled, N-dimensional arrays.

Large RSTS have opened new possibilities for understanding land surface dynamics and human-environment interactions but require specialized methods for big data handling and analytics (Sudmanns et al., 2019). Hence, M1.T2 is focused on large datasets of RSTS, thereby establishing a solid foundation for working with such data in subsequent modules. The Theme summarizes major EO missions, data archives, and options for efficient data query and access. Moreover, it overviews general computing strategies and facilities for large RSTS. Different Jupyter Notebooks provide practical tips for dealing efficiently with large RSTS using Python (e.g., employing parallel and out-of-core computations). Moreover, it is shown how to access satellite image TS via a Spatio-Temporal Asset Catalog (STAC) or via the Python API of GEE cloud computing environment (Gorelick et al., 2017).

Monitoring natural and anthropogenic phenomena with RS very often relies on an investigation of discrete categories of landcover, land surface processes or other phenomena. Thus, automated classification of such target categories in RS data is a crucial task that is increasingly applied also to RSTS. Therefore, M1.T3 deals with TS analysis based on classification, which can be approached either (i) in a multitemporal fashion to track categories or discrete objects through time or (ii) enhancing the classification robustness and discriminative capability by exploiting temporal information derived from a time series. The practical parts of the Theme cover these two approaches at the example of seasonal snow cover monitoring and landcover classification based on spectral-temporal metrics (as input features for a machine learning classifier), respectively.

When studying human-environment interactions it is often important to determine the timing, rate, and spatial distribution of land surface change, and to characterize these changes regarding their magnitude, type, or direction. Dense RSTS open new possibilities for change detection and analysis, as they essentially provide for every spatial unit (e.g., pixel) a series of observations, with each observation containing the value of a variable at a specific point in time. The fluctuation of these values with time can be seen as a trajectory in variable space (Figure 2). M1.T4 introduces trajectory-based views on remotely sensed variables and overviews the main approaches to land surface monitoring and change detection. In a practical example, the course participants learn how to extract, process, and visualize spectral-temporal profiles (trajectories) from a Landsat image time series using Python and GEE. It is shown how the characteristic Normalized Difference Vegetation Index trajectory of a disturbed forest site can inform about the timing of disturbance.

Various RS systems typically resolve different phenomena (depending on their spatial, spectral, and temporal resolution) or can only capture a specific phenomenon adequately if their complementary data is fused. Hence, the objective of M1.T5 is to establish a general understanding of the motivation, needs, and challenges of fusing multi-modal datasets to exploit their full information content. It outlines data fusion approaches at different levels and overviews a selection of methods commonly used for combining RSTS.

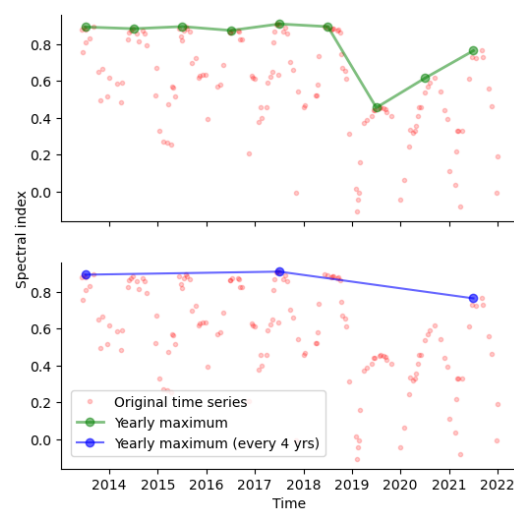


Figure 2. Example of a spectral trajectory. The yearly maxima of a vegetation index indicate a land surface change in 2019 (top), whereas this is not well visible in a coarser time series (bottom), illustrating how the detectability of changes depends on the temporal resolution of original or aggregated data.

The last Theme of Module 1 (M1.T6) conveys important methodological principles of validation and accuracy assessment for RS analyses. The Theme outlines potential reference data sources, explains appropriate accuracy metrics for regression and classification, respectively, and points to critical issues in validating RSTS analysis. In an exercise, the accuracy assessment of a time series based landcover classification (produced in M1.T3) is practiced. With this broad introduction to approaches and methods of RSTS analysis M1 sets a solid foundation for working on the more specific topics of M2 to M4.

2.2 Module 2: Satellite Multispectral Images Time Series Analysis

The first sensor-specific Module is oriented towards the utilization of TS of satellite multispectral (MS) data. Continuous acquisition of satellite data over many decades (e.g., Landsat for over 50 years) makes this Module harness the advantage of the most extensive TS within the course. The revisit time of satellites is also important here. Missions such as Sentinel-2 or PlanetScope provide current data every 5 or even every day, respectively. To fully leverage the temporal potential of such data, it is essential to prepare and process it properly and consistently, ensuring the utmost accuracy in the analysis results. The selection of data and methods hinges on the study's scale — whether local, regional, or global — and the required time interval to accurately capture phenomena of interest, such as the effects of hurricanes, climate change, or the peak of the growing season, in either inter-annual or intra-annual data.

The general structure of the Module 2 (M2) includes five Themes with theoretical lessons, practical exercises, and three research-oriented case studies (S):

- M2.T1 Principles of multispectral imaging
- M2.T2 Temporal information in satellite data
- M2.T3 Image processing workflow
- M2.T4 Multitemporal classification
- M2.T5 Vegetation change and disturbance detection
- M2.S1 Monitoring tundra grasslands in Krkonoše/Karkonosze Mountains
- M2.S2 Effects of pollution in Ore Mountains
- M2.S3 Forest disturbance detection in Tatra Mountains

The first Theme (M2.T1) is general introduction of MS satellite data properties and several processing methods. Both spatial and spectral resolutions of data are discussed here. The concept of visual interpretation of satellite images as well as the use of multiple spectral bands is presented. Subsequently, vegetation indices (e.g., Normalized Difference Moisture Index or Normalized Burn Ratio) and data transformation products (e.g., Tasseled Cap or Principal Component Analysis) calculations are explained. Selected satellite sensor characteristics and data archives are shown followed by the discussion of advantages and limitations of satellite multispectral imaging. The exercise in this Theme is related to various objects and phenomena interpretation in Tatra Mountains based on data from different resolution sensors (MODIS, Landsat 8 OLI, Sentinel-2 MSI, PlanetScope and in addition, orthophoto) in QGIS software. Knowledge gained will help in the creation of own reference datasets in further exercises (M2.T2, M2.T4, and M2.T5) and the third case study (M2.S3).

M2.T2 emphasizes the aspect of satellite data temporal resolution. The importance of constantly acquiring satellite data, the different mission durations and revisit time of selected sensors and various definitions related to categories or time components of data are presented (Figure 3). Two main types of multitemporal analysis on such data are discussed: classification and change detection. Various tools and algorithms related to these types are introduced. They are detailed further in subsequent themes. The exercise of M2.T2 aims to identify events of changes and attribute change agents to detected occurrences based on trajectories of spectral indices and images chips. The exercise is implemented in the R programming language thus introducing it to the M2.

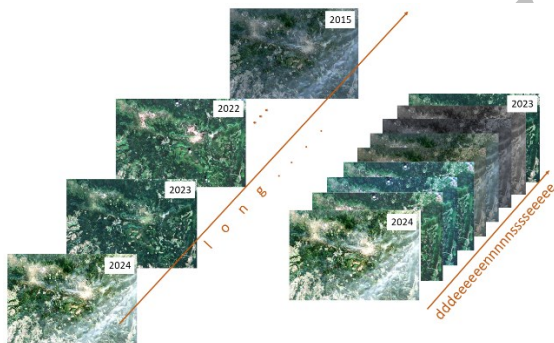


Figure 3. Long and dense time series data examples (source of Sentinel-2 image: European Space Agency - ESA).

In M2.T3 students learn about the entire satellite data processing workflow. In the theoretical part, radiometric and geometric corrections, unwanted areas detection and masking, as well as missing information reconstruction processes are presented. Then, data fusion and harmonization/normalization processes across different sensors are covered. Various practical tools and algorithms (e.g., specific sensor processors, R packages) are linked. In the exercise different processing ‘pipelines’ are presented with the use of GEE platform. They consist, among other things, of image collections filtering, cloud/shadow masking and composite creation methods. The proper processing of data in each pipeline presented in this exercise is crucial for the quality of input data used in further exercises (M2.T4, M2.T5) or case studies (M2. S1- M2. S3, Figure 4).

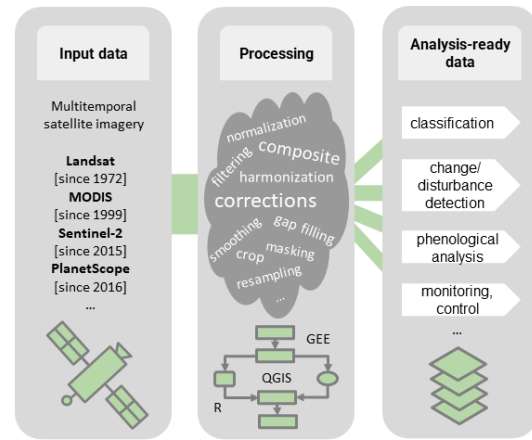


Figure 4. Module 2 overview – from input data to analysis-ready data.

M2.T4 and M2.T5 are oriented on specific thematic analysis. In M2.T4 semi-automatic multitemporal classification is introduced, where elements such as multitemporal reference datasets (e.g., from existing databases), algorithms (e.g., commonly used machine learning and algorithms that take into account spectral-temporal dependencies in their construction), ways for selection of the best terms of data acquisition related to feature selection are described in detail. Results validation and accuracy assessment (in conjunction with complementary content of related Theme M1.T6) based on satellite data research examples are shown. In the exercise, a Random Forest (RF) classifier implemented in R is used to classify land cover on multitemporal dataset of Sentinel-2 data. Variable importance analysis is also conducted. M2.T5 offers a comprehensive theoretical background for detecting changes and vegetation disturbance/recovery on TS. Different types of changes, variables used to detect them, and complex algorithms are presented, following trajectory-based analysis introduced in M1.T4. The assessment of the accuracy of the results and sample analysis products are also shown. Several selected algorithms are explained in detail. The exercise focuses on the use of the Landsat-Based Detection of Trends in Disturbance and Recovery (LandTrendr) algorithm (Kennedy et al., 2010, 2018) implementation in GEE to investigate disturbance events in Tatra Mountains vegetation over 39 years (1984-2022).

The presented case studies are connected to the recent research activities in three mountain areas. M2.S1 is aimed at vegetation mapping in Karkonosze/Krkonoše Mountains. Different scenarios of subalpine and alpine vegetation classification with focus on grassland class are performed here with Support Vector Machines (SVM) in R and Sentinel-2 data from different dates in the growing season (Wakulińska and Marcinkowska-Ochtyra, 2020). Reference data polygons were collected during field campaigns in Polish Karkonosze National Park. M2.S2 explores the development of forests in the Ore Mountains affected by air pollution, utilizing Landsat time series data since 1984 (based on Kupková et al. 2018, Mišurec et al. 2016). The study is accessible through an Earth Engine App. The last case study (M2.S3) shows Tatra Mountains vegetation and recovery during 1984-2022 period with the use of the author's Threshold- and Trend-based Vegetation Change Monitoring Algorithm (TVCMA, Ochtyra et al., 2020). In this area strong winds and bark beetle outbreaks are the primary causes of disturbances and such abrupt and gradual changes can be detected. The obtained results present, among other features, year of detection and trendline.

Module 2 of this course provides a thorough understanding of multispectral satellite data, blending theory with practical applications. It leverages tools dedicated to processing of large remote sensing time series to prepare analysis-ready data used in subsequent exercises. Custom scripts and the ability to learn and create novel algorithms and tools enable students to interpret and analyse multispectral data effectively. As publicly available data is used, it is easy to transfer the given examples to their own research.

2.3 Module 3: 3D/4D Geographic Point Cloud Time Series Analysis

The focus of Module 3 is on 3D/4D geographic point cloud TS analysis (Figure 5). The analysis of surface activities and structural dynamics 4D point cloud data has become an integral part of close-range EO. Geographic 3D point clouds are increasingly available due to substantial developments in sensor devices, computation power and reductions in cost. Current trends in research and industry (e.g., low-cost 3D photogrammetry and RPAS-borne sensing) demonstrate the importance of geographic point clouds as a data source. From highly accurate LiDAR sensors to off-the-shelf smartphones, different devices can be used to generate 3D point clouds, capturing ‘snapshots’ of a landscape at different spatial scales and varying data quality.

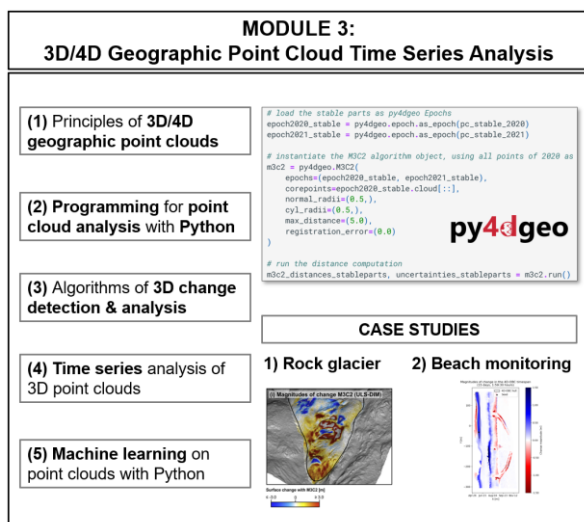


Figure 5. Overview of Module 3 - 3D/4D Geographic Point Cloud Time Series Analysis.

In this course 4D (3D + time) point clouds are defined as hyper-temporal point clouds, which capture the ongoing surface dynamics with high frequency during the change is ongoing (Eitel et al. 2016, Vos et al. 2022). With repeated acquisitions, time series of 3D point clouds contain valuable information about changes (e.g., elevation, object geometry) in a scene. Module 3 is designed to be research-oriented and to receive updates from the research frontier for practical and real-world applications. The central learning goals are to be able to understand the main concepts of multitemporal point clouds and to practically analyse such point clouds with Python scripts.

Module 3 consists of five Themes containing theoretical lessons with exercises, self-evaluation quizzes and two research-oriented case studies:

M3.T1 Principles of 3D/4D geographic point clouds

M3.T2 Programming for point cloud analysis with Python

M3.T3 Principles and basic algorithms of 3D change detection and analysis

M3.T4 Time series analysis of 3D point clouds

M3.T5 Machine learning-based 3D/4D point cloud analysis

M3.S1 Case study: Multitemporal 3D change analysis at an active rock glacier

M3.S2 Case study: Time series-based change analysis of sandy beach dynamics

In the first theme (M3.T1) 3D/4D point clouds as data model are introduced and fundamental point cloud operations and concepts of change analysis are explained following the key literature of Otepka et al. (2013) and Eitel et al. (2016). The main learning outcome of the theme is the knowledge what kind of data is to be analysed.

In the second theme (M3.T2) the goal is to learn fundamental skills in Python programming (scripts and Jupyter Notebooks) for point cloud analysis, which are the basis for the following themes and exercises. This includes reading and writing of point clouds (e.g., LAS files), neighbourhood operations, plotting and statistics of point cloud features and rasterization for elevation model generation.

In the third theme (M3.T3) point cloud-based change analysis and different approaches to that are explained. Based on the concept of a general change analysis workflow – including alignment, change quantification, uncertainty analysis and change representation – the students will be able to perform a complete point cloud-based change analysis on their own.

The fourth theme (M3.T4) is dedicated to TS of point clouds. Their acquisition, spatiotemporal information and recent methods for TS-based point cloud change analysis are explained such as the approaches of 4D Objects-By-Change of Anders et al. (2020) and unsupervised clustering by Kuschnerus et al. (2021).

The final theme (M3.T5) explains recent methods of machine learning on point clouds using Python. Classification and regression examples are provided and supported with respective codes, including the computation of standard local point cloud features (e.g., planarity, roughness, slope).

The two case studies, 1) rock glacier monitoring (Zahs et al. 2019) and 2) beach monitoring (Vos et al. 2022), are ongoing research projects with recent publications available to get more detailed information. The aim of the case studies is to provide a comprehensive bundling of all themes and to show how 3D/4D monitoring projects can be implemented in analysis workflows that the participants have learned in Module 3.

Open datasets comprising samples of 4D point cloud data are provided for each case study together with a tutorial on data processing using open software packages (Python libraries, CloudCompare). Further, open data from national airborne LiDAR surveys are used for exercises. Thereby, a variety of point cloud sources (UAV and airborne laser scanning, UAV photogrammetry, permanent terrestrial laser scanning) and applications (assessment of glacier retreat, high-mountain rock glacier changes, coastal dynamics) are covered in the module.

2.4 Module 4: Airborne Imaging and Laboratory Spectroscopy Time Series Analysis

The last Module of the E-TRAINEE course focuses on the processing of airborne/RPAS hyperspectral (HS) imagery and

spectra measurements acquired with portable spectroradiometers in the field or in the laboratory. It shows the link between spectroscopic measurements and plant functional traits that are commonly used as indicators of ecosystem state and/or disturbances and their response to climate change and other human-induced environmental changes.

Following the general course structure, Module 4 consists of five Themes containing theoretical lessons with exercises and three research-oriented case studies:

M4.T1 Principles of imaging and laboratory spectroscopy

M4.T2 Aerial/RPAS hyperspectral data acquisition and pre-processing

M4.T3 In-situ and laboratory spectroscopy of vegetation

M4.T4 Machine learning in imaging spectroscopy

M4.T5 Temporal vs. spatial and spectral resolution

M4.S1 Seasonal spectral separability of selected grass species of the Krkonoše Mts. tundra ecosystem

M4.S2 Discrimination of selected grass species from time series of RPAS hyperspectral imagery

M4.S3 Seasonal dynamics of flood-plain forest

In the first theme (M4.T1), the basic terms (e.g., spectroscopy, hyperspectral data cube, spectral library) are defined. Examples of satellite/airborne/RPAS sensors for imaging spectroscopy and spectroradiometers used for field and laboratory measurements, including their technical specifications, are given. The objective of the connected exercise is to get familiar with the EnMap-Box software package and to explore the spectral responses of selected grass species and their changes within a vegetation season. HS imagery of a test plot from the Krkonoše Mts. tundra acquired with a Nano-Hyperspec® camera, is used for this exercise.

Geometric and illumination conditions to be considered during the airborne/RPAS flight planning and pre-processing steps leading to orthorectified and radiometrically corrected hyperspectral imagery are summarised in the theme M4.T2. The exercise points out the geometric distortions of overlapping hyperspectral images acquired with an RPAS push broom sensor (Nano-Hyperspec®) equipped with a middle-class GNSS/IMU (RMSE of 1.7 m on the check points; Červená et al., 2020) and their rectification based on an orthoimage with a horizontal accuracy of 3 cm.

The third theme (M4.T3) is fully devoted to foliage, its parameters and spectral response measured in-situ or in laboratory. In three lessons, the students learn in detail about:

- vegetation reflectance curve and its relation to the leaf/foliage structure and its biophysical properties,
- spectroradiometer measurements on the leaf level with a contact probe and an integrating sphere on an example of a spectroradiometer ASD FieldSpec® (supplemented with videos),
- laboratory and in-situ measurements of vegetation parameters/ leaf functional traits (e.g., chlorophyll, leaf mass per area, water content).

The exercise of M4.T3 aims at comparing selected foliage spectra acquired with a contact probe and an integration sphere.

Classification methods explained and practiced on multispectral imagery in Modules 1 and 2 are further elaborated in the theme M4.T4. The emphasis is on exercises where four supervised classification methods suitable for hyperspectral imagery can be practiced and compared. Temporal features are not considered,

but the classification results can be further analysed if applied on single time horizons or a multitemporal dataset (cf. Modules 1 and 2). First, a subpixel classification using linear unmixing in EnMAP-Box with different approaches to endmember extraction is explained. The next two exercises guide through Python scripts for SVM and RF classifications and point out lines where the classifier parameters can be changed/tuned. In the last exercise, three types of convolutional neural networks (CNN) – 1D (i.e., convolution is performed only along the spectral dimension), 2D (convolution only in the spatial – row, column – dimension), and 3D (convolution both in the spatial and along spectral dimension) are introduced. The CNN architecture is based on the U-Net (Ronneberger et al. 2015). The Python scripts can be run either on local machines, or in the cloud using Google Colab.

The influence of temporal, spectral, and spatial resolution on the discrimination of selected vegetation species/communities and monitoring their changes is discussed in the theme M4.T5. It contains only the theoretical part.

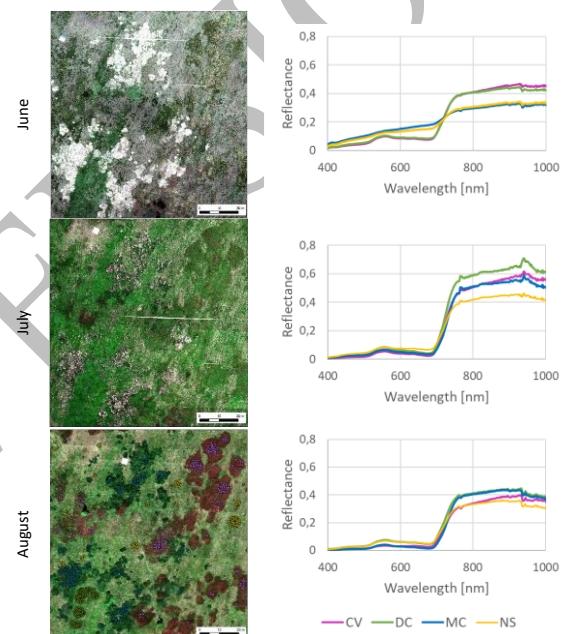


Figure 6. Spectral signatures of selected grass species derived from Nano-Hyperspec® imagery collected in the Krkonoše Mts. tundra (50.7308N, 15.6889E) in 2020. Coloured dots in the image from August show position of 450 random pixels per species from which the average spectra were calculated. CV – *Calamagrostis villosa*, DC – *Deschampsia cespitosa*, MC – *Molinia caerulea*, NS – *Nardus stricta*.

The presented case studies are connected to the recent research activities in the Krkonoše Mts. National Park aiming at monitoring changes in vegetation occurrence and its state (Kupková et al., 2023). In both cases, RPAS images acquired with the Nano-Hyperspec® sensor are utilised. The first case study (M4.S1) is based on the work of Červená et al. (2020) and it evaluates the separability of four grass species at image level by statistical tests (Welch's t-test, Wilcoxon rank test) for each wavelength and by separability analysis (Jeffries-Matusita distance) in R (Figure 6). The classification accuracy of selected tundra grasses derived from mono- and multitemporal (within one season) hyperspectral RPAS imagery is compared in the second case study (M4.S2). Moreover, the influence of the pre-processing step, comprising minimum noise fraction (MNF), on

classification accuracy is also discussed. The RF classification is carried out in R. Thus, this case study combines knowledge gained especially in the themes M4.T4 and M4.T5 and it is based on the research carried out by Kupková et al. (2023). The last case study (M4.S3) builds on the theme M4.T3. Its objective is to relate spectral, biochemical and portable chlorophyll meter measurements to assess seasonal changes in leaf chlorophyll content of floodplain forest tree species.

3. COURSE IMPLEMENTATION

The course is presented as a website, which gets automatically generated from a GitHub repository. The repository holds the course contents in the form of markdown (.md) and Jupyter (.ipynb) files. To limit the repository size, large datasets are presented on Zenodo and videos on YouTube. The main branch of the repository holds course contents, while the website is generated into the "gh-pages" branch on merge of feature branches to "main" (as shown in Figure 7). When generating the final website, markdown and Jupyter Notebook files are converted into HTML using MkDocs (mkdocs.org) with the Material theme (squidfunk.github.io/mkdocs-material). Other functionality is provided by the "search" and "mkdocs-jupyter" plugins, which provide functionality for search and direct Jupyter Notebook inclusion into the website navigation bar. The functionality has also been extended with a JavaScript for quizzes at the end of lessons. Although MkDocs is geared primarily towards technical project documentation, it has proven to be suitable for the general course website as well.

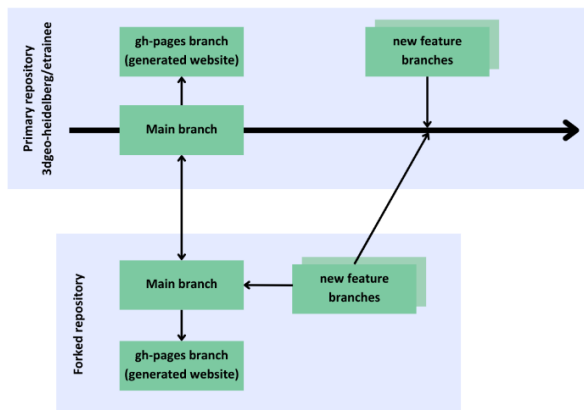


Figure 7. E-TRAINEE GitHub branch structure and intended workflow for using a forked repository for specific course.

When teaching the course, forking the main ETRAINEE repository is recommended, as shown in Figure 7. Forking creates a stable version of the website, which is independent of potential changes in the main branch. This system also makes it simple to improve the course when teaching it. Any potential changes can be easily transferred back into the main repository, without worrying about disrupting anyone else who may be teaching the course at the same time.

For future course development, there is potential in actively using GitHub Issues for gathering student feedback, thus letting the students contribute their ideas directly. To improve or extend the E-TRAINEE course, the repository also contains templates, which make the process of building new modules easy. Potentially extending the course with new modules is also made to be simple, as new people can build modules based on their expertise via new git branches.

4. DISCUSSION AND CONCLUSIONS

The international collaboration resulted in the development of comprehensive, open, and research-oriented learning materials beyond the curricula of geography and geoinformatics in many universities. It can be used by students and practitioners from other disciplines working with RSTS on different spatial scales. It is based on a multidisciplinary approach connecting themes from computer science, geography, surveying, ecology, plant biology, and environmental studies. It combines well established as well as latest technologies (satellite vs. UAV sensing, multispectral vs. hyperspectral sensing and 3D point clouds), methods of artificial intelligence (machine and deep learning) but it also stresses how to use these technological developments to understand environmental changes. The important part is the focus on improving and increasing digital literacy of participants, i.e., understanding algorithms of data processing, programming, and automatic analysis of large geographic data sets. This fact is important but often underestimated, not only in geographical studies. The course benefits from the research projects of the four involved universities and thus has the potential to be a successful example of knowledge transfer from research to research-oriented education.

The course offers high flexibility, both for self-studying or studying with a tutor. Emphasising compulsory and optional sections helps the students, who are new to the topic, gaining the expected level of knowledge without demotivating them by getting overwhelmed with details. They have the possibility to return to the optional parts later, according to their specific needs. Different levels of detail and difficulty might also attract attention of professionals who seek to update or deepen their knowledge in RSTS analysis. Providing quizzes and example solutions to the exercises gives the students an opportunity to carry out a self-evaluation of their work or to just look at the expected results if they are not interested in performing all the steps on their own.

From the point of view of the development team, carrying out a transnational project has brought much more than an opportunity to create comprehensive course content that would not be possible without the synergy of all research groups. Among the main benefits are:

- sharing knowledge, skills, and best teaching practices,
- saving time and resources for learning material development,
- having a base for collaborative online teaching and follow-up activities such as summer schools,
- stimulating new ideas for further collaboration in education and research,
- initiating student mobility among partner universities.

The course is available from the following website <https://3dgeo-heidelberg.github.io/etrainee/>. It is published under the CC BY-SA 4.0 license, and the associated code is under the MIT license. Starting from the academic year 2023/24, the course will be implemented in the MSc curricula in geography/geoinformatics of the involved universities (Charles University, Heidelberg University, University of Innsbruck, and University of Warsaw) in different forms. The course materials will be continuously updated as all four institutions will actively use the course, and new releases will be made available for public use. Its design allows for an easy extension of new modules, themes, or case studies.

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