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Article

Scale-specific Hyperspectral Remote Sensing Approach in Environmental Research

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Summary: Hyperspectral remote-sensing data can contribute significantly to data analysis in research, opening up a wide spectrum for fields of application due to geometrical as well as spectral characteristics, e.g. in water status analysis, in the classification of vegetation types, in the classification of physical-biochemical vegetation parameters, in classifying soil composition and structure, and in determining large-scale soil contamination. Hence, there is a tremendous demand for hyperspectral information. However the use of commercial hyperspectral data is associated with a number of problems and a great deal of time and effort is required for research using hyperspectral data that spans different spatial and/or hierarchical as well as temporal scales. As a result few investigations have been conducted on the causal relationships between imaging hyperspectral signals and meaningful vegetation variables over a longer monitoring period. At the Helmholtz Centre for Environmental Research (UFZ) Leipzig a scale-specific hyperspectral remote sensing based on the sensors AISA-EAGLE (400–970 nm) and AISA-HAWK (970–2500 nm) has been set up. On three different scales (plot, local and regional) intensive investigations are being carried out on the spatio-temporal responses of biophysical and biochemical state variables of vegetation, soil and water compared to the hyperspectral response. This paper introduces and discusses the scale approach and demonstrates some preliminary examples from its implementation.

Zusammenfassung: Hyperspektraldaten stellen für die Forschung eine sehr bedeutsame Auswertegrundlage dar, da sie aufgrund ihrer geometrischen als auch spektralen Eigenschaften eine Vielzahl unterschiedlicher Anwendungsgebiete, z.B. Gewässerzustandserfassung, Vegetationsklassifizierungen, Charakterisierung physikalisch-biochemischer Vegetationsparameter, Strukturierung und Zusammensetzung des Bodens, Erfassung von großflächigen Bodenkontaminationen, eröffnen. Es besteht somit ein sehr hoher Bedarf an Hyperspektralinformationen. Der Einsatz von kommerziellen Hyperspektraldaten ist jedoch mit einer Vielzahl von Problemen verbunden. So sind Forschungen hinsichtlich unterschiedlicher räumlich/hierarchischer als auch zeitlicher Skalen mit Hyperspektraldaten nur sehr schwer möglich, andererseits existieren nur wenige Untersuchungen zu kausalen Zusammenhängen zwischen abbildenden Hyperspektralsignalen und gesuchten Vegetationsvariablen über einen langen Monitoringzeitraum. Am Helmholtz Zentrum für Umweltforschung (UFZ) Leipzig wurde eine skalenspezifische hyperspektrale Fernerkundung auf Grundlage der Sensoren AISA-EAGLE (400–970 nm) und AISA-HAWK (970–2500 nm) etabliert. In drei unterschiedlichen Maßstabsbereichen (Grundstück (plot), kommunal (local) und regional) werden intensive Untersuchungen zum raum-zeitlichen Verhalten von biophysikalischen und biochemischen Zustandsgrößen von Vegetation, Boden und Wasser gegenüber hyperspectral response durchgeführt. Im Artikel wird der Skalenansatz vorgestellt, diskutiert und erste Umsetzungsbeispiele gezeigt.

1 Introduction

The application of optical remote sensing data from airborne and satellite sensors has been well established in environmental research for more than three decades (Schaepmen et al. 2009). It provides a state-of-the-art method for a variety of monitoring issues requiring

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spatial information of the Earth's surface. Depending on the specific data product and ancillary data, improvements in ecological, hydrological and climate modelling have been possible over a wide range of spatial scales. Thereby, the reliability of final information or quantifications depends mainly on sensor-specific limitations in terms of their spectral and spatial characteristics. Modern airborne imaging hyperspectral sensors open up many new different fields of applications thanks to their high geometric (< 5 m) and spectral (~ 5 nm) characteristics, e.g. monitoring the state of aquatic ecosystems, quantifying biodiversity, retrieving biophysical-biochemical vegetation parameters, assessing soil structure and composition, recording soil contamination over larger areas. With the launch of the German hyperspectral satellite mission EnMAP (Environmental Mapping and Analyses Program) that is foreseen for 2015, a new imaging spectrometer data format in terms of its spectral (6.5–10 nm) and geometric (30 m × 30 m spatial resolution) characteristics will be available (Stuffler et al. 2009). The EnMAP data product on the regional scale and the possibility of available multi-temporal data will enable monitoring issues to be realized on the regional scale.

Knowledge about the retrieval of vegetation parameters, e.g. leaf area index, pigments, photosynthesis activity, is generally performed with analytical, simulation or experimental studies. Since, the latter requires tremendous effort in terms of cost, time and technical infrastructure, leaf and vegetation canopy radiative transfer models (RTM) became a valuable method for investigating the relationship between narrow-band spectral features and plant or vegetation canopy parameters (Jacquemoud et al. 2009). This will be able to be applied to a wide range of species and has the advantage that it can be applied from the field level upwards. However, overlapping and confounding internal factors, e.g. heterogeneity of the vegetation canopy parameters, and external factors, e.g. the observation angle, that influence the signal, can constrain the implementation of RTM with studies involving field-scale heterogeneity since RTM assume homogeneity. Empirical analyses have therefore been criticized for their lack of generality, which physical-based approaches promise to overcome. Since, quantitative reflectance data are directly applied as input variables, empirical approaches linking spectral vegetation indices (VI) and vegetation parameters are less influenced by atmospheric correction factors but are rather more site-specific with atmospheric and surface characteristics at the time of data acquisition (Houborg & Anderson 2009). However, to validate quantitative studies using empirical or physical based approaches in general, a tremendous effort is required from ground truthing campaigns. In the case of fluctuating internal factors, e.g. phenological stages, and external factors, e.g. illumination conditions, spatial and spectral observation characteristics, affecting the canopy reflectance between the imaging spectrometer campaigns, the established methods, parameter characteristics, e.g. pigment value range or coefficients are not directly transferable to other applications, study sites or phenological stages. In terms of transferring methods and awareness of important correlations, there is in particular a lack of knowledge about spatial scale-dependent information, which needs to be verified much more with real data and naturally occurring land surface heterogeneity effects.

In the setting of TERENO (terrestial environmental observatories, www.tereno.net, Zacharias et al. 2011) imaging hyperspectral airborne remote sensing plays a key role in long-term monitoring on different scales and in different regions. The Helmholtz Centre for Environmental Research UFZ delivers knowledge about complex systems and relationships in the environment by interlinking the natural, social and human sciences. In order to guarantee a comprehensive process-oriented research in landscapes and ecosystems, imaging spectrometer sensors that are able to conduct in-house optical remote sensing have been made available. The imaging hyperspectral remote sensing is based on the two sensors; AISA-EAGLE (400–970 nm) and AISA-HAWK (970–2500 nm) – Airborne Imaging Spectrometer for Applications (Mäkisara et al. 1993) developed by SPECIM (Spectral Imaging LTD., Finland). The sensors, which have a high geometric (0.5–5 m) and spectral (2.3–8.5 nm) resolution, are used on different observation platforms in order to be able to obtain multi-scale (spatial) spectrometer data. A rotating mirror device enables use of the scan line sensors on a lifting platform and in laboratory experiments. The permanent availability of the sensors guarantees data acquisition at any required time, e.g. a specific phenological stage, on the landscape scale using different aircrafts.

2 Research Issues and Background

Knowledge acquired about the sensitivity of hyperspectral reflectance data and plant or vegetation canopy parameters is generally acquired on a specific spatial observation scale. Many studies used field spectrometer data to analyze appropriate relationships or to develop new spectral vegetation indices (Bannari et al. 2007). Relationships retrieved from radiative transfer models should be interpreted or transferred with caution and the parameterization, e.g. value ranges, observation settings, applied during the experiments should be taken into account (Haboudane et al. 2004). One issue that is often not addressed is the influence of the spatial observation scale on the reflectance signal in terms of its sensitivity to retrieved biochemical and biophysical parameters. Hence, it is generally not clear with which accuracy quantitative results can be expected from potential stakeholders. Therefore the need arises to analyze real data at different spatial observation scales and to test recently proved methods, e.g. radiative transfer models, empirical models, and neural networks, in terms of their performance.

Furthermore there is a lack of knowledge about the temporal behaviour of plant and vegetation canopy reflectance characteristics over entire growing cycles from experimental data on the landscape scale. Such basic monitoring experiments promise progress in understanding the dynamics of overlaying effects in particular, i.e. different plant and vegetation parameters. Simulation experiments are very valuable in providing basic understanding, although a validation of real data cannot be substituted to finally understand the effect of combined effects under real conditions and how these will change over the growing season.

The outlined issues are very difficult to address in research practice and when focusing on the use of commercial hyperspectral data, the following obstacles arise:

- Data is generally collected at one specific spatial resolution due to costs and the time management of the partner operating the sensor.
- Multi-temporal datasets are difficult to obtain over one growing cycle in the case of limited sensor availability, e.g. competing campaigns in terms of time, with appropriate clear sky conditions. For instance, the HyMap (Hyperspectral Mapper) campaigns in Germany over recent years were generally conducted in July and August. A temporal monitoring of different vegetation parameters is therefore not possible over the year or an entire growth cycle.
- Furthermore, as a result of the research question and the key parameters of interest, the requirements of the ground truthing design are comparatively clear. Field campaigns can often take many months or even years to plan because of the high effort of organisation required in terms of staff, e.g. technicians, students, instrumentation, e.g. mobile plant and canopy analyser, laboratory resources, e.g. pigment extraction, and ancillary information, e.g. thematic maps.

To provide realistic and high quality datasets and make progress in remote-sensing analyses, imaging spectrometer data from the landscape level, airborne and ground "segment" are still not a separable union. Therefore, the key issues of the monitoring design presented in this paper are i) to analyze the sensitivity of hyperspectral data to a wide range of physiological parameters and phenological stages on different spatial scales, ii) to acquire knowledge about the temporal dynamics of the above, and iii) to improve our understanding about the overlaying effects for retrieving parameters on "real" data.

To address a wide range of these issues, a scale-specific remote sensing experiment was set up, which is presented in the following section.

3 Scale-specific Monitoring Methods

The concept of the scale-specific remote sensing experiment at the Helmholtz Centre for Environmental Research (UFZ) in Leipzig/Germany is based on data sampling from three different observation scales, which are presented in Fig. 1. Scales 1 to 3 are outlined in more detail in section 3.2. Scale 4, which represents the final landscape scale will not be discussed further in this paper.

All measurements were carried out with the same imaging hyperspectral sensors which are described in section 3.1. Selecting spatial ground resolutions enables algorithms and training datasets to be transferred between scales. During the laboratory measurements we were able to obtain the same footprint (geometric resolution 50 cm × 50 cm) as at the landscape level (scale 3).

3.1 *Sensor Characteristics*

Tab. 1 summarizes the main sensor properties of the UFZ's hyperspectral sensors. The relevant spectral and geometric sensor properties that are required depend on the research objectives and the spatial observation scale.

3.2 *Experimental Design*

Scale 1 – Long term laboratory vegetation monitoring experiments, plot scale (plant level, vegetation canopy)

To examine causal relationships between imaging hyperspectral signals and single plant or vegetation canopy parameters as well as their overlaying effects, the only appropriate method is to conduct controlled laboratory experiments. By conducting such experiments, the spectral response of vegetation under different arbitrary scenarios, drought stress, CO_2, heavy metal pollution, the effect of pesticides etc., can be studied at frequent intervals, e.g. twice a week. Consequently, there is tremendous potential for model development and validation to retrieve plant and vegetation canopy parameters (leaf area index, chlorophyll a/b ratio, photosynthesis activity, biomass, carbon/nitrogen ratio, soil moisture). Furthermore, a major advantage of this kind of laboratory experiments is that measurements are always carried out under the same basic conditions such as light source and general geometric observation properties (2 × 1000 W halogen lamps, fixed angle of incidence and distance sensor-object). A darkroom measuring approximately 3 × 3 × 3 m^3 made of light-

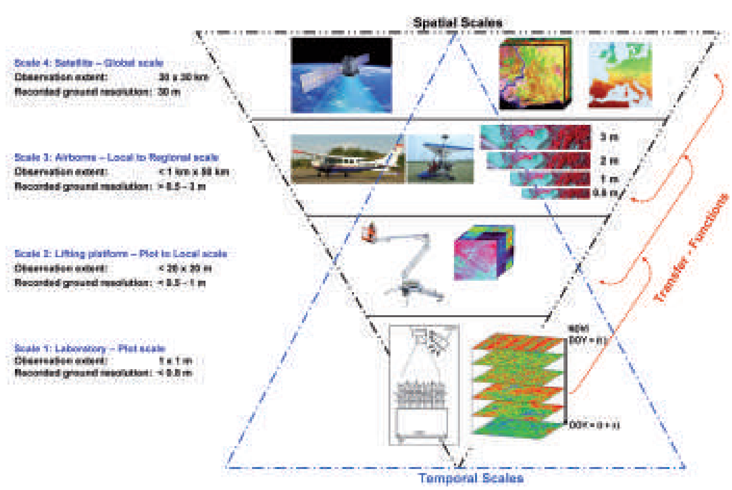

Fig. 1: The concept of monitoring the biophysical–biochemical vegetation variables on different spatial and temporal scales with the imaging hyperspectral sensors AISA-EAGLE/HAWK (modified after LAUSCH et al. 2012).

Tab. 1: Characteristics of the hyperspectral sensors from the UFZ – AISA-EAGLE / HAWK.

Sensor head	**AISA-EAGLE VNIR**				**AISA-HAWK II SWIR**
Weight	11 kg				18 kg
Dimensions (L/W/H)	380/220/55 mm				220/275/470 mm
Spectral range	400 – 970 nm				970 – 2500 nm
Spectral resolution	2.9 nm				8.5 nm
Max. spatial pixels	1024				320
Camera	CCD Camera				MCT Camera
SNR	350:1 – 1400:1 (depending on band configuration)				800:1 (peak)
Spectral binning options	1x	2x	4x	8x	
Spectral bands	488	252	122	60	254
Spectral sampling/ band	1.25 nm	2.3 nm	4.6 nm	9.2 nm	
Image rate	30	40	60	85	
Focal length	23 mm	18.5 mm		9 mm	22.5 mm
FOV	29.9 degrees	36.7 degrees		62.1 degrees	24.0 degrees
Swath width	0.53 x altitude	0.66 x altitude		1.20 x altitude	0.43 x altitude
Ground resolution at 1000 m altitude	0.52 m	0.65 m		1.2 m	1.34 m
Additional parts					
Mirror scanner	Mirror scanner for local applications (field plots)				Mirror scanner for local applications (field plots)
FODIS	Fiber Optic Down welling Irradiance Sensor				Fiber Optic Down welling Irradiance Sensor

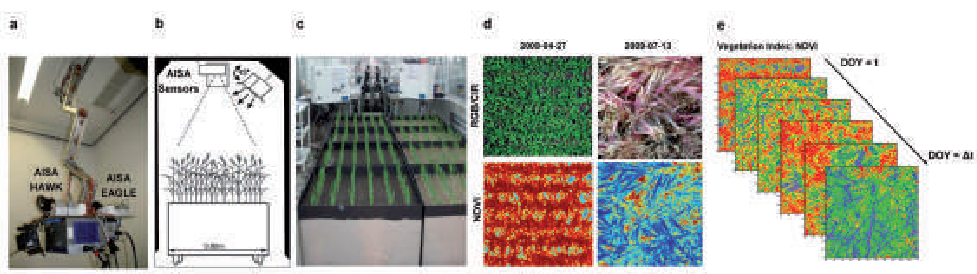

Fig. 2: Use of the imaging hyperspectral sensor AISA-EAGLE/HAWK in the laboratory, a) technical configuration of AISA-EAGLE/HAWK in a lifting platform on the ceiling, b) construction of the laboratory experiment with imaging hyperspectral sensors, c) vegetation scenarios of spring barley experiment 2009 (DOY 117-201), d) RGB, CIR and NDVI (normalized difference vegetation index) derived from the AISA-EAGLE hyperspectral image of spring barley (2009-04-27, 2009-07-13), e) quantification of vegetation indices derived from imaging hyperspectral AISA sensors – example NDVI.

proof material was set up for the hyperspectral measurements. The use of this darkroom prevents any disruptive factors from having an effect over the entire series of tests. Fig. 2 shows the test set-up in the laboratory and examples of imaging hyperspectral data from the available measurement tests on spring barley under different drought stress scenarios.

Scale 2 – Lifting platform, plot to local scale (vegetation canopy)

Test plots with a surface area of $< 20 \times 20$ m² can be examined using a lifting platform (Fig. 3). Both hyperspectral sensors (AISA-EAGLE/HAWK) are mounted onto the lifting platform at a height of 2–12 m above the vegetation. The aim of these tests is to record the causal relationships between spectral imaging signals and the target parameters measured, e.g. to derive biophysical and biochemical canopy state variables such as LAI (leaf area index), chlorophyll content, vegetation water content or nutrient status of vegetation, under 'in-vitro' conditions. With the lifting platforms a long-term monitoring of different vegetation plots is possible. Furthermore, we can test the influence of different sensor angles, any bidirectional reflectance distribution function (BRDF) effects on the imaging spectral response and establish transfer functions from scale 1 to scale 2.

Scale 3 – Airborne remote sensing, local to regional scale (vegetation, populations, ecosystems)

To provide airborne imaging hyperspectral data for innovative studies related to practice we opted to use a Cessna 207 or Piper for spatially extensive hyperspectral campaigns (Fig. 6) and a microlight aircraft (Trike, D-MUFZ, Fig. 4) as a sensor platform for small scale, e.g. field scale, hyperspectral campaigns. Fig. 4 shows the hyperspectral sensor AISA-EAGLE together with the GPS/INS unit RT3100 (Oxford Technical Solutions LTD., UK) fitted onto the microlight and the microlight itself in operation. The advantages and disadvantages of using a microlight as a sensor platform are listed below.

The advantages of using a microlight are:

- flexibility in terms of time enabling a high repetition rate of data acquisition
- independence from outside bodies in terms of project planning, since pilots and operators are members of the staff of the research institute
- economical use in terms of repairs and maintenance
- its design, enabling a use in a wide range of areas abroad (it can be dismantled and transported in containers together with the sensors)
- recording imaging of hyperspectral data with high spatial (< 0.5 m) and temporal resolution

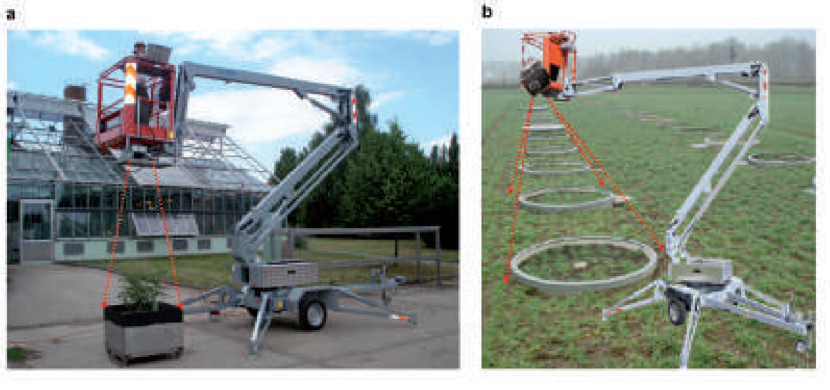

Fig. 3: Using the hyperspectral sensor AISA-EAGLE/HAWK on lifting platforms over a) test plots and b) lysimeters.

Disadvantages of using a microlight are:

- thermal lift affecting the microlight's stability and thus limiting the time of operation during the day
- sometimes difficult handling of the equipment
- limitation of the imaged area (maximum about 10 km²)

Fig. 4: a) AISA-EAGLE (400–970 nm) and GPS/INS-RT3100 mounted onto the microlight aircraft (Trike, D-MUFZ) of the UFZ, b) Microlight aircraft of the UFZ – D-MUFZ, c) Microlight aircraft for recording hyperspectral data – landscape level.

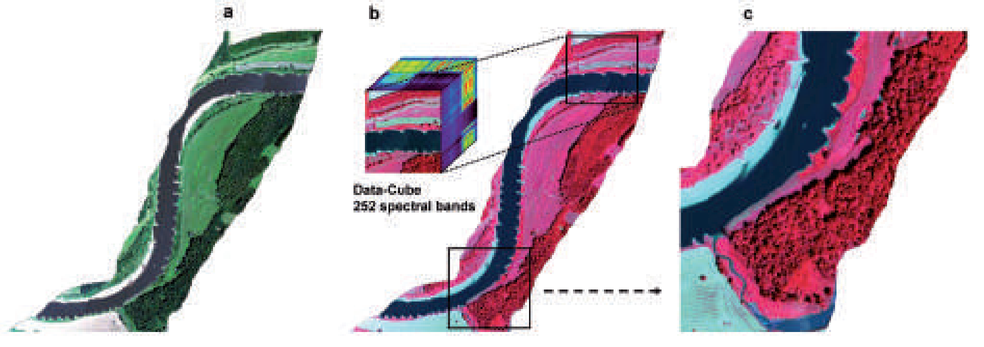

Fig. 5: "Schleusenheger Wiesen" near Dessau recorded 2008-07-03 using the microlight aircraft of the UFZ, images from the hyperspectral sensor AISA-EAGLE, 400–970 nm, 1 m ground resolution, 252 spectral bands: a) RGB-Image, b) CIR-image with data cube, c) CIR hyperspectral image subset.

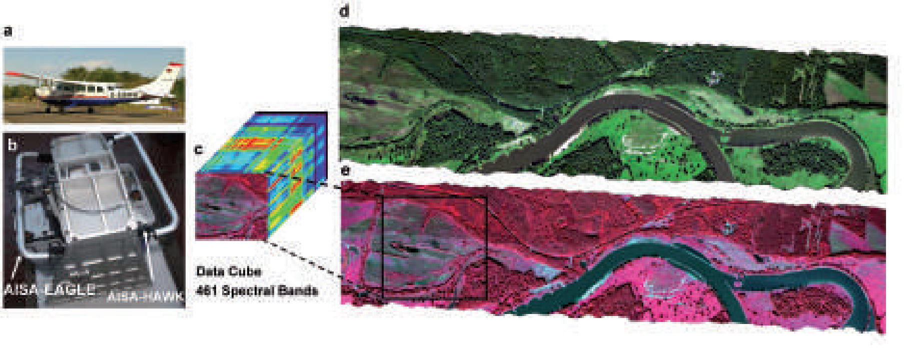

Fig. 6: a) Cessna 207, b) AISA-EAGLE/HAWK Dual sensor mount in the Cessna, c) data cube of AISA-DUAL data, d) and e) "Region Rosslau" – RGB- and CIR-image – taken from the hyperspectral sensor AISA-EAGLE/HAWK, 400–2500 nm, 2 m ground resolution, 461 spectral bands, date of recording 2010-09-23 with a Cessna 207.

4 Preliminary Results

To emphasize the importance of observation characteristics on the final results based on hyperspectral data, the following sections provide some simple examples on this issue.

4.1 *Spectral Response of Imaging vs. non Imaging Spectrometer Data*

Over a three month period from April 27, 2009 to July 20, 2009 (DOY 117-210, 84 days), spectral data (imaging hyperspectal data – AISA-EAGLE and non-imaging ASD Spectrometer) and vegetation parameter measurements (LAI, Chlorophyll SPAD-502, canopy height, vegetation water content, C/N content of vegetation) were recorded twice a week. Details on the experimental design can be found under 3.2 as well as in Lausch et al. (2012). For spring barley various vegetation indices were investigated for the AISA-EAGLE imaging spectral data as well as for the ASD non-imaging hyperspectral data with regard to their suitability for the model in terms of various biochemical and biophysical vegetation parameters over the entire vegetation period of 84 days.

We are able to assume that the differences in the model results for the vegetation index GNDVI (R800-R550) do not result from a change in biochemical or biophysical parameters to the vegetation, soil or atmosphere due to the fact that both measurements taken using the imaging and non-imaging hyperspectral sensors were carried out under the same basic conditions and within minutes of each other. We therefore assume that there are other factors influencing the spectral behaviour of both sensors. The different spectral responses from both sensors could be explained by several factors: (I) Differentiated sensor-specific mapping characteristics and the specific sensor characteristics of AISA-EAGLE (Whiskbroom-Scanner) and ASD. (II) The calibration of the non-imaging spectrometer (ASD) with the imaging spectrometer that sometimes proves to be insufficient or is not carried out at all, leading to inaccurate measurements and consequently a repetition of errors in terms of sensor models and validation with hyperspectral data (at scales 3 and 4). (III) The inner geometry, structure and pattern of the vegetation is strongly reflected by the hyperspectral response. This is much stronger compared to the spectral response of biochemical and biophysical vegetation parameters (chlorophyll-content, vegetation-water content, protein content). (IV) Both sensors take a different "footprint" of the object, e.g. vegetation, even though the field of view (FOV) from the objective is comparable. (V) The varying degree of dependency of the spectral signal on the date (DOY) or change in phenology, i.e. for the vegetation index GNDVI over the entire vegetation period of 84 days (DOY 117-201).

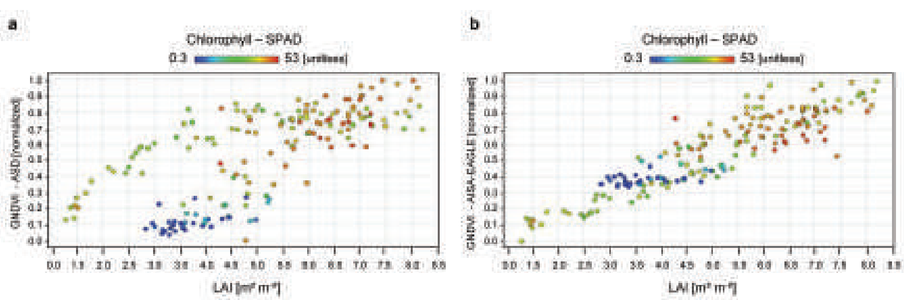

Fig. 7: Relationship between vegetation index GNDVI and LAI (leaf area index) obtained from laboratory measurements with a) non-imaging spectrometer ASD and b) imaging spectrometer AISA-EAGLE for spring barley. The colours show Chlorophyll SPAD-502 content (unitless) over the entire growing season (DOY 117-201).

4.2 *Monitoring of Vegetation Parameters and Spectral Response over an entire flowering Period with the Imaging Hyperspectral Sensor*

Another study describes the same experimental approach and the results from using the imaging hyperspectral sensor AISA (400–970 nm, 252 spectral bands) under controlled and comparable conditions in a laboratory to study the spectral response compared to different biochemical and biophysical vegetation and soil parameters (LAI, Chl-SPAD-502, CCC, GWC, vegetation height, C/N-content) over an entire flowering period of spring barley (Fig. 8 a–f). The spectrum of each hyperspectral image was used to calculate a range of vegetation indices (VI's) that have been recorded in the literature. Furthermore, all combinations of the 252 spectral bands were tested to calculate a range of vegetation difference indices (VI's$_{(xy))}$ and reflectance value indices (R$_{(X)}$) at the central wavelength (*x* nm) of each band (R$_{(x)}$). For all three index types we examined the relationship with the vegetation variables measured on the ground by using a cross-validation procedure.

4.3 *Estimating phenological Stages of Barley from Time Series Measurements with an Imaging Hyperspectral Sensor*

The aim of another application for the approach presented in this paper was to set up a model to predict the different phenological BBCH macro-stages of barley in the laboratory on the plot scale and to transfer the best model found to predict the phenological stages of barley to the landscape scale. To classify phenology eight vitality and phenology-related vegetation parameters were obtained like for example leaf area index (LAI), Chl-SPAD, C-content, N-content, C/N-content, canopy chlorophyll content (CCC), gravimetric water content (GWC) and vegetation height (VH) at the same time that all imaging spectral measurements (AISA-EAGLE) were conducted. These biochemical biophysical vegetation parameters were examined according to their suitability to record images of various phenological BBCH macro-stages of barley (**B**iologische Bundesanstalt für Land- und Forstwirtschaft, **B**undessortenamt und **CH**emische Industrie) (Biologische Bundesanstalt für Land- und Forstwirtschaft 2001, Hack et al. 1992). The predictive models were developed and

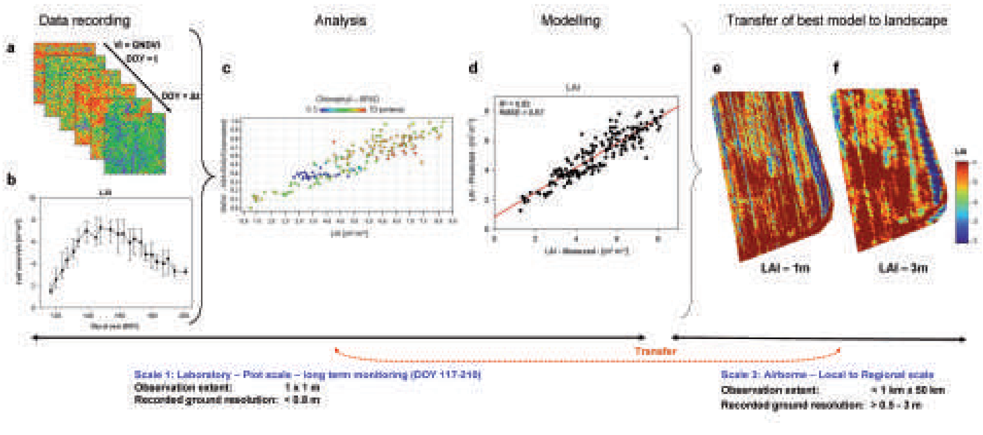

Fig. 8: Long-term vegetation monitoring experiment on scale 1 – laboratory – plot scale of spring barley, DOY 117-210, a) vegetation index GNDVI – obtained from the imaging hyperspectral data – AISA-EAGLE, b) recorded biophysical vegetation parameter – leaf area index (LAI), c) GNDVI and LAI derived from the imaging spectrometer AISA-EAGLE, d) best regression model for estimating LAI quantified from GNDVI – AISA-EAGLE, e) transfer of the best regression model for estimating LAI – GNDVI to scale 3 – airborne – regional scale, modelling LAI in 1 m f) the same for 3 m, recording date 2010-06-15.

tested using four different vegetation index types: (I) Published VIs, (II) Reflectance VIs as well as (III) $VI_{(xy)}$ formula combinations and (IV) a combination of all VIs.

To investigate a differentiation between the phenological BBCH macro-stages of spring barley, many well-known published VIs were included in the analyses. Our results show that the best prediction of the different macro-stages results from a combination of the published VIs PRI (photochemical reflectance index), renormalized difference vegetation index (RDVI) as well as the water band index (WBI) with a classification accuracy of 82.39 %. The best predictive model of the phenological BBCH macro-stages was obtained from a comprehensive model using all three VIs – Published VIs, Reflectance VIs and a combination of formula VIs with a classification accuracy of 84.80 %. The best predictive model was subsequently used on airborne AISA-EAGLE hyperspectral data to model the phenological macro-stages of barley on the landscape level (Fig. 9 e,f).

4.4 *Spatial Heterogeneity Analysis using an Imaging Hyperspectral Sensor*

There are very few empirical studies that use hyperspectral data to support the hypothesis of deriving land surface variables from different spatial scales. The goal of the current study was to investigate the influence of differently recorded spatial scale hyperspectral data on the reflectance behaviour and heterogeneity of the vegetation. The hyperspectral sensors AISA-EAGLE/HAWK were mounted onto an aircraft to record spectral signatures over a very short time sequence of a particular day. The reflectance measurements were collected at three different spatial resolutions ranging from 1 m to 3 m. The NDVI was ascertained from all image data. The NDVI heterogeneity of all images was compared based on methods of variography. Variogram models of the NDVI heterogeneity were obtained from the recorded spatial resolutions 1 m, 2 m and 3 m for grassland and deciduous forest (Fig. 10 a–e).

The results showed that the spatial NDVI patterns of different recorded and scaled data do not correspond among each other. The

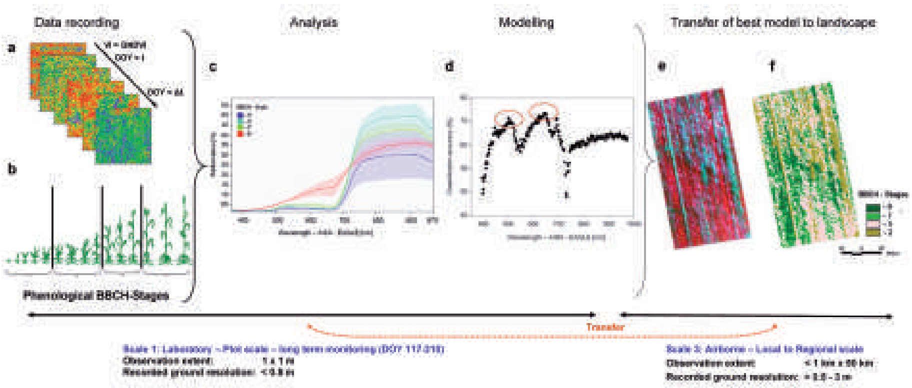

Fig. 9: Long term vegetation monitoring experiment on scale 1 – laboratory – plot scale of spring barley, DOY 117-210, a) quantification of different vegetation indices based on imaging hyperspectral data – AISA-EAGLE, b) BBCH-macro-stages of vegetation, c) spectral response from AISA-EAGLE for the BBCH macro-stages 2, 5, 7 and 9 for barley, d) predictive power of each spectral reflectance value ($R_{(X)}$) at the central wavelength (x nm) of each band of the imaging AISA-EAGLE spectrometer to classify the phenological BBCH stages 2, 5, 7 and 9 of spring barley, transfer of the best model for predicting BBCH macro-stages to scale 3 – airborne – regional scale, e) airborne AISA-EAGLE hyperspectral data – 1 m spatial resolution, recording date 2010-06-15, shown as a CIR-image, f) modelling the BBCH macro-stages based on the best model from scale 1 – plot scale.

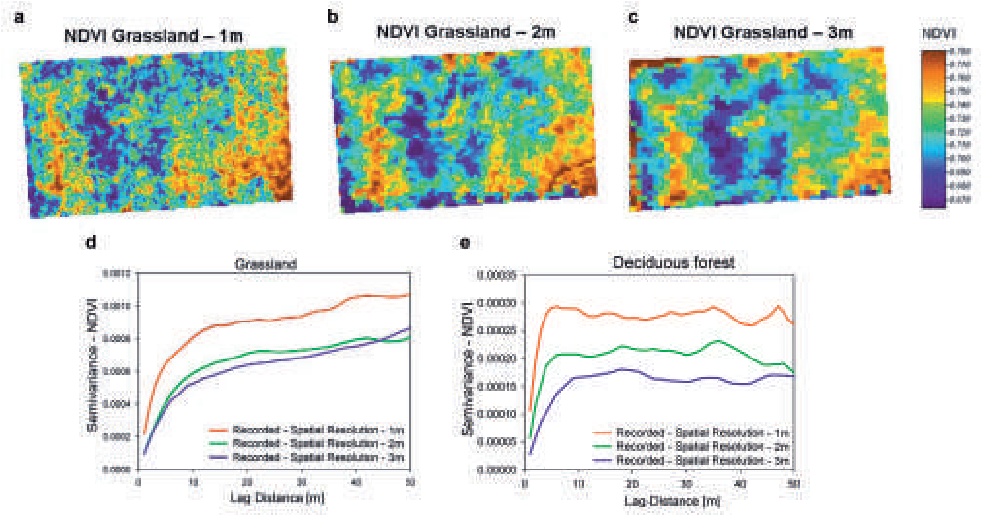

Fig. 10: Calculation of NDVI from the AISA-EAGLE/HAWK (DUAL) hyperspectral data recorded with different ground resolutions, recording date 2010-09-11, a) 1 m, b) 2 m, c) 3 m, Semivariance – NDVI for d) grassland and e) deciduous forest – derived from hyperspectral data (AISA-EAGLE/HAWK) recorded at a spatial resolution of 1 m, 2 m and 3 m.

NDVI patterns of different spectral data that were recorded showed slight changes. The implications behind these findings are that we need to exercise caution when interpreting and combining spatial structures and spectral indices derived from satellite images with differently recorded geometric resolutions.

5 Conclusion and Outlook

The objective of this paper was to propose our scaling method of combining hyperspectral remote sensing data from different spatial and temporal scales and to point out the potential of using only one and the same imaging hyperspectral sensor as the input to plot the local, regional and landscape level.

The use of one hyperspectral sensor at different temporal and spatial scales ("One Sensor At Different Scales" – OSADIS Approach, Lausch et al. 2012) offers the unique advantage of a true comparison of data at different spatial scales as well as the transfer of process information obtained from long-term *in-situ* monitoring investigations. It is possible to investigate the effect of different spatial, temporal, spectral and directional scales of land surfaces i.e. heterogeneity, vegetation phenology or wavelength. Confounding factors such as the phenology of vegetation, BRDF measurements from vegetation geometry, and a number of dynamic atmospheric effects etc. can specifically be eliminated, as such parameters can be considered to be relatively constant within the time frame of 2–3 hrs.

With our preliminary results we were able to show that it is not only possible to combine sensors with different characteristics, e.g. AISA-EAGLE and ASD, geometrically, spectrally as well as temporally but also to apply these process investigations over different scales.

A comparability of measuring equipment with different imaging optics and sensors is extremely difficult. Spectral sensors have different (I) recording characteristics, (II) spectra and spatio-temporal recording characteristics as well as (III) FOV. Moreover, an attempt to introduce some conformity results in BRDF as well as species-specific spectral responses, which result from a difference in sensors and not from a difference in processes. It is therefore extremely difficult to separate these effects.

By using the One Sensor At Different Scales Approach we are able: a) to develop suitable stress-controlled long-term vegetation indicators for selected target variables like for example LAI, chlorophyll, photosynthesis activity, water content, nutrient content etc. b) to realistically transfer the models obtained to the landscape level c) to record imaging hyperspectral information at different spatial scales, whereby we are able to achieve a true comparison of the structural and process results obtained d) to minimize the existing magnitude of errors from geometrical, spectral and temporal effects due to sensor- and temporal-specific differences e) to carry out a top-up and down-scaling through the determination of scale-dependent correction factors and transfer functions. f) With our scale approach (OSADIS) we attempt to understand scales, structures, patterns and their temporal changes better and in more depth and are able to describe or quantify them at all.

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