ASSESSING THE POTENTIAL OF THE FUTURE ENMAP MISSION FOR THE MULTISEASONAL RETRIEVAL OF BIOPHYSICAL LAND SURFACE PARAMETERS USING MULTISENSORAL AIRBORNE SPECTROSCOPY

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ABSTRACT

With the upcoming hyperspectral satellite mission EnMAP, a powerful instrument for the generation of Earth Observation Data will soon be available. EnMAP for the first time will enable the retrieval of multiseasonal hyperspectral observation series from space. For agricultural applications of EO data, this capability offers the highly relevant opportunity of retrieving the seasonal development of vegetation parameters not only for single plots, but with regional coverage. Information on the seasonal development of crop parameters thereby is one key to agricultural information products in the context of precision farming. Preparing for the data streams that will have to be expected from EnMAP and it follow-up missions, this study helped to compile multiseasonal hyperspectral data through an exhaustive airborne campaign during the summer of 2012. The study shows, how the hyperspectral data series may be used for the derivation of the seasonal development of vegetation parameters, such as leaf area index and canopy chlorophyll content. Thereby, the capability of hyperspectral data for the retrieval of vegetation parameters with the help of inverted canopy reflectance models is assessed.

1. INTRODUCTION

To ensure the sustenance of a growing world population, traditional farming methods are stretched to their limits. As a consequence, the importance of precision farming, i.e. an optimized and highly mechanized production of agricultural goods, is increasing. Hyperspectral remote sensing provides technology to derive biophysical land surface parameters, which are vital for improved land surface management, more precisely compared to multispectral methods [1]. From 2017 onwards, the upcoming German satellite mission EnMAP (Environmental Mapping and Analysis Program) will deliver high quality spaceborne hyperspectral data with a spatial resolution of 30 meters [2]. EnMAP will not only allow for the multiseasonal monitoring of dynamic vegetation development, but will also enable hyperspectral monitoring on the regional scale. Due to its off-nadir (+/-30°) pointing capability, EnMAP will theoretically be able to achieve a revisit time of up to 4 days.

The Department of Geography of the LMU Munich is involved in the preparation of algorithms that are designed to fully exploit these special capabilities of EnMAP for innovative agricultural applications of EO data.

Some of the algorithms developed in that context are and will be published within a software product called EnMAP-Box, entirely dedicated to the use of the EnMAP data. This EnMAP-Box is a platform-independent software interface designed to process hyperspectral remote sensing data. It is intended to enable scientists, who are interested in working with EnMAP data, to perform basic but nonetheless state of the art image operations. The authors so far contributed three modules to the EnMAP Box that are of relevance in an agricultural context:

- **Agricultural Vegetation Indices (AVI)**

A collection of 65 hyperspectral vegetation indices that were selected based on an extensive literature survey. The indices are grouped according to their target variables: structure (13), chlorophyll (26), carotenoid (5), plant water content (8), dry mass (9) and fluorescence (4).

- **Analyze Spectra Integral (ASI)**

A module based on the concept of Continuum Removal, which is particularly suitable for the estimation of chlorophyll and water content of vegetation. The algorithm compares the integral of a defined region of the spectrum to the area enclosed by a spectral envelope that is adopted between the two specific border wavelengths. The module is dynamic, i.e. the border wavelengths may be defined by the user.

- **Advanced Statistical Evaluator (ASE)**

A collection of 17 statistical indicators, which are suitable for both, correlating two sets of point data as well as correlating two image data sets for the quantification of pattern agreement. The indicators are divided into three groups: Error indices (e.g. root mean squared error, RMSE), correlation-based measures (e.g. coefficient of determination, R^2), dimensionless indicators (e.g. Nash-Sutcliffe Efficiency, NSE). The aim is to provide a tool that may assist with improving the comparability of scientific results within the user community.

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Apart from these contributions to the EnMAP-Box, methods and algorithms for the derivation of agriculturally relevant land surface parameters are developed to prepare for an efficient processing of the future satellite data. In regard to the increasing importance of precision farming and the capabilities of EnMAP, which will be able to deliver periodic products (near-nadir revisit in 21 days), one of the most important research questions is assessing the potential of EnMAP for the retrieval of multiseasonal information on the spatial distribution of biophysical land surface parameters from hyperspectral image data without the availability of in situ data.

A special focus thereby may be directed to the retrieval of leaf area index (LAI) and canopy chlorophyll content (CCC), as they are important variables for the monitoring of the current status of plant or canopy physiology respectively. Since EnMAP data will not be available before 2017, airborne spectroscopy is widely used for the development of retrieval strategies, as it also was the case for this study. Applying commercially available imaging spectrometers, however, is limited by the sensor availability and often involves high costs, which makes it almost impossible to generate a multiseasonal data set for a specific test area based on commercial sensors alone. To overcome this limitation, a cost effective series of airborne imaging spectrometers called AVIS (Airborne Visible and Near Infrared Spectrometer) has been developed at the Department of Geography of the LMU Munich [3]. With the third generation sensor, AVIS-3, which is equipped with two camera systems (VNIR and SWIR1) covering a spectral range from 470-1700 nm, four acquisitions were successfully obtained during the course of the vegetation period of 2012 over a 12 km² large test site in Southern Germany (Neusling, Lower Bavaria). The multiseasonal campaign was complemented by two additional acquisitions from the airborne sensor HySpex, which is operated by the German Aerospace Center (DLR). Parallel to the imaging flights, in situ data were gathered, resulting in more than 500 measurements of leaf area index, leaf chlorophyll content, soil moisture, plant height and phenological status of different crops (winter wheat, winter barley, rapeseed, maize, sugar beet).

The challenge of estimating biophysical parameters from hyperspectral data without the use of in situ data leads to the application of physically-based methods, such as the inversion of canopy reflectance models. Quite in contrast to empirical-statistical models, such as vegetation indices, which have to be calibrated with in situ data, if they are to be used for the derivation of actual vegetation variables, physically-based methods may potentially be applied without in situ data available. Due to their intrinsic dependency on in situ data, empirical models may deliver high-quality results, but at the same time suffer from a very limited transferability. In addition to this limitation, empirical methods are sensitive to anisotropy effects that are resulting from a variable sun-sensor-target-geometry within the airborne data. Physically-based approaches may explicitly account for these anisotropies, so that illumination angle dependent nonlinearities, instead of being an error source, may serve as additional information, which can be integrated into the retrieval strategy, thereby improving the overall retrieval quality. For the physically-based retrieval of land surface parameters, the combined leaf optical properties model (PROSPECT5) and canopy bidirectional reflectance model (4SAIL) PROSAIL [4] was used, which simulates realistic reflectance data for homogeneous vegetated surfaces [5].

To estimate biophysical parameters from spectral reflectance data, the canopy reflectance models must be inverted [6]. There are several inversion techniques described in the literature, which differ in computation speed, robustness and performance. The most common inversion techniques for parameter retrieval are numerical optimization algorithms, artificial neural networks (ANNs) and look-up tables (LUTs) [7]. Because of its simplicity, transparency and robustness, the LUT approach was chosen for this study. PROSAIL was used in forward mode for the simulation of spectral reflectances, based on a specific range of parameter combinations and thus to build up a spectral library, consisting of the spectra themselves and their corresponding parameter configuration. Based on a cost function, which searches for the lowest distance between two spectra, each measured spectrum of a data set is assigned to the respective spectrum from the LUT, which most closely resembles the measured reflectance. Consequently, it is assumed that the underlying parameter setting behind the modelled spectrum must be valid for the measured spectrum and thus represents the biophysical variables to be retrieved.

As with neural networks, an advantage of LUTs is that a large part of computing time is done before the actual inversion is carried out [8]. However, in contrast to numerical optimization and artificial neural networks, the LUT approach admits a global search and is in this way not endangered to be trapped in local minima [6].

Numerous studies, e.g. [9], [10], show that LUTs often are more robust and generate higher accuracies compared to other approaches. Furthermore, LUTs have the advantage to represent a relatively simple method, their content being precisely defined [8]. This allows for the comprehension also of intermediate results, while neural networks often are criticized as black-boxes. Compared to iterative optimization algorithms, the LUT method is significantly less time consuming [11]. However, it is not as fast as a neural network.

The quality of the inversion results then depends on several factors: the quality of the measured signal, the number of bands that is considered for the inversion, the applied cost function, the averaging method and the solution of the ill-posed problem, which may occur if the best fit happens not to be unique. This paper therefore explicitly addresses the findings on optimal inversion strategies that were obtained during the multiseasonal derivation of leaf area index and canopy chlorophyll content from airborne hyperspectral data.

2. MATERIALS & METHODS

2.1 Multiseasonal Campaign 2012

As data basis for this study, a multiseasonal campaign in a 3x4 km area around Neusling / Lower Bavaria was realized. During the summer of 2012, six airborne data sets could be acquired, mostly covering arable surfaces. While for four imaging flights AVIS-3 (LMU) was used, two flights were realized with the HySpex sensor (DLR; Tab. 1).

Table 1. Data acquisitions and corresponding solar zenith angles (SZA) of the multiseasonal campaign 2012

Acquisition Date	Sensor	SZA (°)
April, 28th	AVIS-3	42
May, 8th	HySpex	45
May, 25th	AVIS-3	39
June, 16th	AVIS-3	28
August, 12th	HySpex	42
September, 8th	AVIS-3	45

While HySpex is a commercially available imaging spectrometer, AVIS-3 is an in-house development of the Department of Geography at the LMU Munich. The platform-independent, light-weight sensor is built from commercially available components. Power supply is possible via two car batteries, thus rendering the system independent from the platform generator and thus avoiding any electrical disturbances that might evolve from a direct electrical connection between sensor and platform. For the imaging flights carried out in the frame of this study, a propeller-driven Dornier-27 served as platform, which was kindly provided by the aviation group of Fürstenfeldbruck, Germany. The preprocessing of the airborne data, which also was carried out at LMU for the AVIS-flights, includes analysis of the spectral properties, sensor calibration, geometric correction, spatial data fusion, radiometric calibration and finally spectral data fusion. Having gone through all corrective steps, AVIS-3 data consists of 197 spectral bands, covering a spectral range from 477-1704 nm at a spectral resolution of 5.8 nm (< 994 nm) and 6.6 nm (> 994 nm) respectively. The ground sampling distance in this case was 4 m. An important step of the preprocessing is the consideration of viewing angle information. For this purpose, sensor zenith and azimuth angle were stacked to the spectral data as additional bands (Fig. 1).

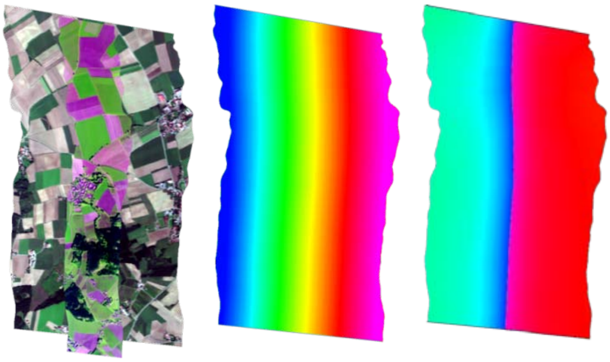

Figure 1. AVIS-3 data layers, consisting of spectral information resulting from two camera systems (VNIR projected in true color, SWIR in coloured infrared; left). sensor zenith angle (middle) and sensor azimuth angle (right). Please note that the SWIR sensor has a lower swath width compared to the VNIR instrument.

If this meta information is available in conjunction with the respective solar zenith angle for the acquisition, the illumination geometry can be traced for each pixel. Fig. 2 shows an AVIS-3 scene after the preprocessing.

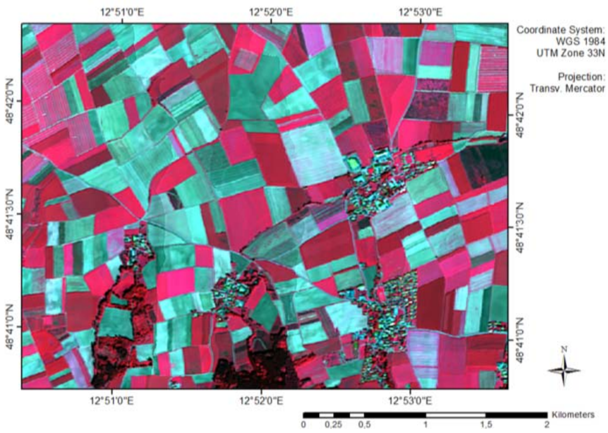

Figure 2. Completely preprocessed AVIS-3 image mosaic (8 stripes), projected in colored infrared (Sept 8th 2012)

In order to address questions of scale in scope of the EnMAP mission, the imagery of both sensors was also spectrally and spatially resampled to simulate the properties of the future EnMAP HSI.

Parallel to the imaging flights, an extensive in situ campaign was carried out. More than 500 measurements of biophysical variables, such as leaf area index (LAI), leaf chlorophyll content (LCC), soil moisture, phenology and plant height complete the multiseasonal campaign. This data is of major importance, as it not only may serve for the calibration of empirical retrieval models, but may also serve for the validation of physically-based retrieval approaches, such as the applied canopy reflectance model.

2.2 Look-Up Table Inversion

Based on randomly chosen parameter configurations, where each parameter range is bounded and normally distributed around a focus of most probable values, the LUT is accumulated before the actual inversion. The quality of a LUT depends on the range, discretion levels and amount of parameter configurations as well as on an optimal search strategy. Although Weiss et al. evaluated an optimal LUT size of 100 000 as a good compromise between computer resources requirements and retrieval accuracy [12], another approach was chosen in this study.

Based on the given parameter combination and a fixed illumination and viewing angle setting, a LUT consisting of 50 000 spectra and their corresponding parameter configuration is generated. To take the possible variations of the illumination geometry into account, the LUT is generated repeatedly for several classes of observer zenith and azimuth angles. The step size of zenith angles thereby was 5°, covering a range from -25° to +25°. The required range was determined by the highest and lowest observer zenith angle in all available images. For the azimuth angle, a step size of 10° in a range from 0° to 180° was chosen, so that all observer angles contained in the image data were covered. Finally, a selection of LUTs is calculated, each considering the respective solar zenith angle of each of the six imaging flights. In the case of the six flights that are part of this study, four iterations were sufficient, because two times solar zenith angles turned out to be almost identical for two imaging flights. Thus, the finally compiled LUT library consists of 50 000 (parameter-based) * 11 (zenith angle classes) * 19 (azimuth angle classes) * 4 (sun zenith angles) = 41 800 000 spectra and their corresponding parameter settings.

2.3 Model Inversion

Although, the advantage of hyperspectral data surely lies with the possibility to examine an almost continuous spectrum, a band selection was performed as a first step towards an optimized inversion strategy. It was found that not all of the initial 197 bands of AVIS-3 may successfully be used for the inversion, mostly due to two reasons. First, bands sensitive in the water vapour absorption range from 1100-1170 and 1300-1500 nm were excluded. Second, bands with a reduced sensitivity, located at the marginal areas of the CCD devices, were equally excluded to ensure only high-quality bands to be used. Thus, 146 bands were finally used in the inversion process. To evaluate the quality of the setting, two additional merely multispectral band combinations were tested, which correspond to the spectral bands of Landsat TM (4 bands within the spectral range of AVIS-3) and the upcoming Sentinel-2 instrument (9 bands within the spectral range of AVIS-3).

The root mean squared error (RMSE) served as cost function, as proposed in several studies, e.g. [7]. Besides the RMSE, we tested the applicability of the Nash-Sutcliffe Efficiency (NSE) as selection criterion, since it precisely indicates the predictive power of models [13]. For the averaging of the spectra that were selected from the LUT, both, the effects of averaging by mean and median were examined.

Probably the most important point for increasing the quality of any inversion process is the solution of the ill-posed problem. Combal et al. explained that for an exact solution of the model inversion, the inversion problem must be well-posed [9]. A physically-based model is well-posed, if (i) a solution exists, (ii) the solution is unique and (iii) the solution depends continuously on the data input. If one of these conditions is not met, the problem will be ill-posed. The ill-posed nature of radiative transfer models (RTM), such as the PROSAIL model that is applied in the context of this study, occurs from the fact that entirely different parameter settings may result in the simulation of very similar spectra.

Other reasons for the ill-posed problem are model uncertainties as well as uncertainties in the reflectance data. While physically-based models may be quite sophisticated, models remain a mathematical abstraction and thus a simplification of reality. In case of the PROSAIL model this means that complex reflectance / scattering behaviour at leaf level cannot be considered by the model in its entirety (yet). Calibration errors and sensor noise in the reflectance data can also lead to uncertainties [14].

The consequence of the accumulated uncertainties for the model inversion is that the best fit may not necessarily lead to the correct parameter specification [10]. In contrast to a well-posed problem, a major consequence of model and reflectance uncertainties at ill-posed problems is that these will not just result in uncertainties in the solution, but rather lead to outright errors. This is due to the fact that the solution space is very widespread and not centred around one true solution [14].

To solve the ill-posed problem, regularization strategies are necessary. One way is the use of a priori information to exclude spectra based on unlikely parameter configurations from the inversion process [9]. A priori information can be provided by knowledge based on in situ data. Since the purpose of this study is the assessment of retrieval strategies that are independent from in situ data, another approach was selected. Thereby, a certain amount of best fits between measured and modelled reflectance signatures are taken into account. Based on the best fit determined by the cost function, a threshold is defined. Within the resulting range, all given parameter combinations are averaged. Richter et al. used the RMSE as cost function and considered the average within less than 10% of the lowest RMSE value [7]. Alternatively, a fixed number of fits can be used instead of a percentage weighting to define the threshold. For this study, various thresholds for the definition of the best fit range were tested, such as percentage weighting as well as the usage of a fixed value. Despite the availability of a priori information, it is a goal of this study to obtain adequate and representative results without dependence on any a priori information. Nevertheless, in situ information served for validation purposes.

2.4 Validation

An extensive validation of the results is important to guarantee comparability with the findings of other studies. Based on a recommendation by Richter et al., a set of optimized statistical measures is chosen [13]: Root Mean Squared Error (RMSE) from the group of error indices; coefficient of determination (R^2), slope (m) and intercept (b) of Theil-Sen regression from the category of correlation-based measures; relative RMSE (RRMSE) and Nash-Sutcliffe Efficiency (NSE) from the category of dimensionless indices. This indicator set ensures the following essential model validation criteria:

- non-dimensionality, to avoid influence from the magnitude of values
- bounded, for effortless comprehension of its meaning
- symmetry, data sets should be interchangeable
- catching the difference in the data to understand the magnitude of the error
- model prediction capability (compared to measurements)

3. RESULTS & DISCUSSION

Based on the different options for the LUT inversion, an extensive evaluation was carried out. Tab. 2 shows a subset of these results, evaluated for leaf area index (LAI).

The overall best result (VIII in Tab. 2) originates from a setting that uses 146 bands, an RMSE cost function, averaging the best 20 fits by mean and under consideration of the illumination geometry (viewing angles).

Directly compared to mere multispectral approaches (I and II in Tab. 2), the use of spectrally continuous data results in a distinct increase in accuracy. The unsatisfying result of III (in Tab. 2) shows the anticipated effect of the ill-posed problem, because only the single best fit was used for estimation. Likewise, the accuracy decreases, if illumination geometry is not considered (IV in Tab. 2). This clearly indicates the strong influence of anisotropies and the potential of physically-based approaches to compensate such disparities. Instead of using a fixed number of best fits, a weighted factor also leads to a decrease of accuracy (V in Tab. 2). Using NSE as cost function (VI in Tab. 2) or median as averaging method (VII in Tab. 2) generates an almost equally high accuracy compared to using the RMSE/Mean method.

Table 2. Validation results for the retrieval accuracy of the variable LAI, depending on the applied spectral setting and inversion technique. The blue frame marks the inversion setting that performed best on the study data.

ID	**I**	**II**	**III**	**IV**
Bands used	4	9	146	146
Cost Function	RMSE	RMSE	RMSE	RMSE
Averaged by	mean	mean	mean	mean
Best Fits (n)	20	20	1	20
Viewing Angles	yes	yes	yes	no
R^2	0.78	0.79	0.68	0.81
m	0.82	0.86	1.01	0.92
b	0.72	0.61	-0.01	0.32
RMSE	0.52	0.51	0.73	0.49
RRMSE	0.14	0.14	0.20	0.14
NSE	0.77	0.77	0.53	0.79
ID	**V**	**VI**	**VII**	**VIII**
Bands used	146	146	146	146
Cost Function	RMSE	NSE	RMSE	RMSE
Averaged by	mean	mean	median	mean
Best Fits (n)	factor 1.5	20	30	20
Viewing Angles	yes	yes	yes	yes
R^2	0.81	0.84	0.85	0.86
m	0.85	0.94	0.94	0.96
b	0.68	0.41	0.26	0.27
RMSE	0.49	0.48	0.43	0.43
RRMSE	0.14	0.13	0.12	0.12
NSE	0.79	0.80	0.84	0.84

Evaluation of chlorophyll content is more challenging, as leaf chlorophyll content (LCC) is difficult to estimate from airborne image data, mostly due to the scale gap between the footprint of the sensors and the size of single leaves. If coupled with LAI information, the canopy chlorophyll content (CCC) may be derived, its scale more corresponding to the observation. However, the result will be clearly predominated by LAI. The results show that an estimation of CCC is still possible with adequate accuracy (Fig. 3).

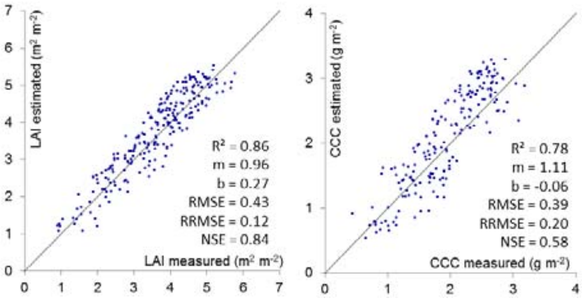

Figure 3. Estimated variables against in situ measurements of leaf area index (left) and canopy chlorophyll content (right)

The results are of high importance to the extent that the method works across the entire season. By considering the illumination geometry within the LUT, the retrieval approach was able to compensate different solar zenith angles as well as different atmospheric conditions.

Since the main focus of this study is the assessment of the potential of the future EnMAP mission for the retrieval of biophysical land surface parameters, the method was transferred to the simulated EnMAP data with its lower ground resolution of 30 m. Fig. 4 shows the LAI estimation of the six simulated EnMAP datasets of 2012. Even at the lower resolution, the model is able to derive the dynamic progression of leaf development of crops during the growing season. Furthermore, land surface heterogeneities are projected as well.

The answer to the question, if the development of specific crops can be monitored, is given in Fig. 5., which shows the progressing development of rapeseed, winter wheat, winter barley, maize and sugar beet projected through the development of leaf area index and canopy chlorophyll content.

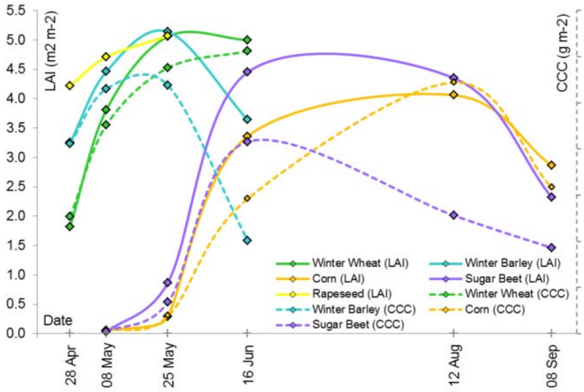

Figure 5. The seasonal course of the estimated parameters indicates the seasonal development of the specific crops.

Fig.5 traces the growth cycles of different crops from emergence until harvest. The development of winter barley, corn and sugar beet shows the typical behaviour of increasing LAI and CCC in spring, a maximum in mid-summer and a decrease due to senescence after maturity. However, the decrease of the actual LAI is overestimated compared to reality, mostly because the

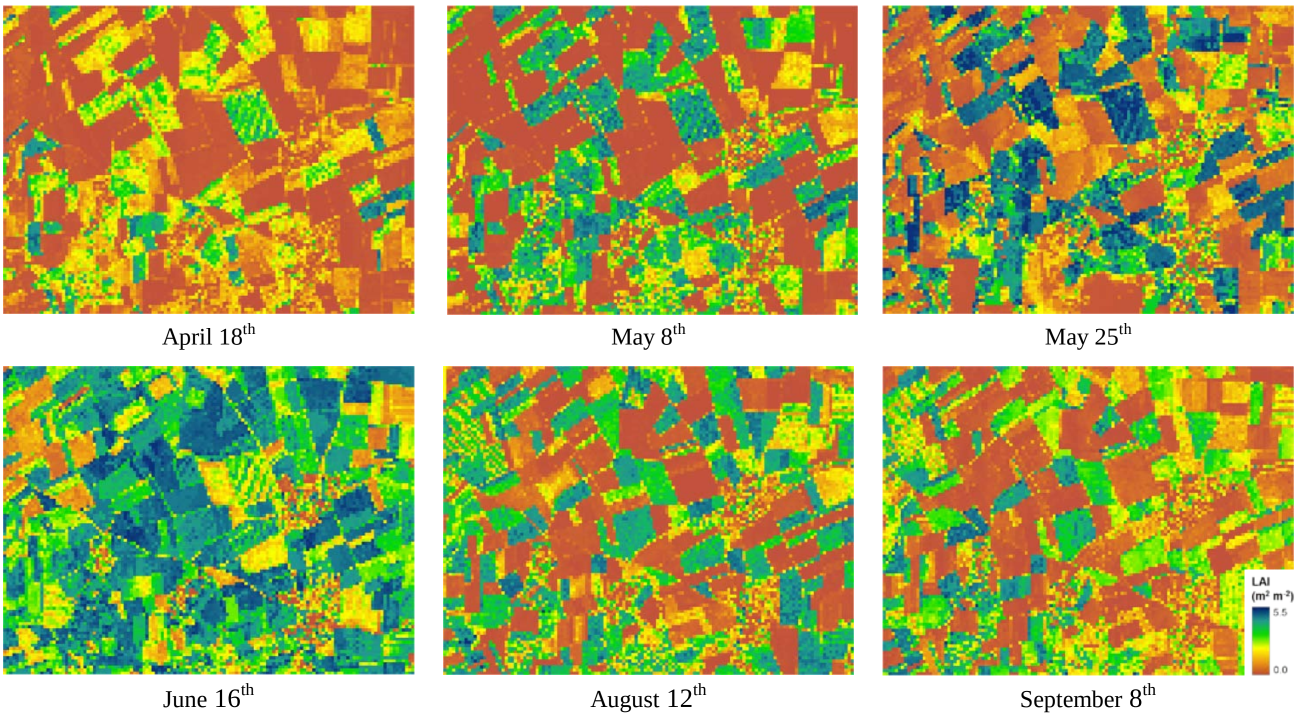

Figure 4: Results of LAI estimation for the test area during the growing season 2012, calculated for the simulated EnMAP images.

model is not able to simulate senescent vegetation, but rather simulates the spectral effects of green LAI, based on the amount of chlorophyll stored within photosynthetically active leaves.

4. CONCLUSIONS

Based on the results presented above, it can be assumed that the LUT inversion of a canopy reflectance model is able to monitor the dynamic development of biophysical vegetation parameters during a growing season without the need of calibration or the use of a priori information respectively. This is of importance in context of the future EnMAP mission, as EnMAP will provide images at a maximum size of 30x1000 km.

The inversion method of averaging the parameters of the best 20 fits between measured and modelled spectra seems to represent a good compromise between eliminating ill-posed spectra without blurring the results. However, there might still be ways to increase the accuracy of the inversion. A larger size of the LUT with finer graduations or the use of a priori information, such as knowledge of the land use and / or phenological status of crops could enable a more precise estimation.

An important finding of this study is the confirmation that hyperspectral data compared to multispectral data results in improvement with respect to the quality of biophysical parameter retrieval, mostly due to the applied curve fittings being more accurate than it is possible with multispectral data. With this in mind, EnMAPs role as a most valuable instrument for future investigations of regional crop development is confirmed. For agricultural purposes, EnMAP will provide data that enables the transfer of sophisticated hyperspectral biophysical variable retrieval techniques from the limitations of airborne acquisitions towards a regional coverage and thus provide useful information in the context of precision agriculture.

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6. REFERENCES

1 Staenz, K. (2009). Terrestrial Imaging Spectroscopy Some Future Perspectives. In: Ben-Dor, E. 6th EARSeL Workshop on Imaging Spectroscopy,Tel-Aviv)

2 Kaufmann, H., Förster, S., Wulf, H., Segl, K., Guanter, L., Bochow, M., Heiden, U., Mueller, A., Heldens, W., Schneiderhan, T., Leitão, P.J., Van Der Linden, S., Hill, J., Buddenbaum, H., Mauser, W., Hank, T., Krasemann, H., Röttgers, R., Oppelt, N. & Heim, B. (2012). Science Plan of the Environmental Mapping and Analysis Program (EnMAP), Deutsches GeoForschungsZentrum GFZ, Scientific Technical Report, 63 pp.

3 Oppelt N & Mauser, W. (2007). Airborne Visible/Infrared Imaging spectrometer AVIS: Design, characterization and calibration. *Sensors* **7**, 1934-1953.

4 Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P. J., Asner, G. P. & Ustin, S. L. (2009). PROSPECT+ SAIL models: A review of use for vegetation characterization. *Rem. Sens. Env.* **113**, 56-66.

5 Jacquemoud, S., Baret, F., Andrieu, B., Danson, F.M. & Jaggard, K. (1995). Extraction of vegetation biophysical parameters by inversion of the PROSPECT+SAIL models on sugar beet canopy reflectance data. Application to TM and AVIRIS sensors, *Rem. Sens. Env.* **52**, 163–172.

6 Darvishzadeh, R., Skidmore, A., Schlerf, M., & Atzberger, C. (2008). Inversion of a radiative transfer model for estimating vegetation LAI and chlorophyll in a heterogeneous grassland. *Rem. Sens. Env.* **112**(5), 2592-2604.

7 Richter, K., Atzberger, C., Vuolo, F., Weihs, P., & D'Urso, G. (2009). Experimental assessment of the Sentinel-2 band setting for RTM-based LAI retrieval of sugar beet and maize. *Can. J. Rem. Sens.* **35**(3), 230-247.

8 Kimes, D.S., Knyazikhin, Y., Privette, J.L., Abuelgasim, A.A. & Gao, F. (2000). Inversion methods for physically-based models. *Rem. Sens. Revs*. **18**(2-4), 381-439.

9 Combal, B., Baret, F., Weiss, M., Trubuil, A., Mace´, D., Pragne`re, A., et al. (2002). Retrieval of canopy biophysical variables from bidirectional reflectance using prior information to solve the ill-posed inverse problem. *Rem. Sens. Env.* **84**, 1– 15.

10 Vuolo, F., Atzberger, C., Richter, K., D'Urso, G., & Dash, J. (2010): Retrieval of biophysical vegetation products from RapidEye imagery. In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium, IAPRS, Vol. XXXVIII, Part 7A, 281-286.

11 Darvishzadeh, R., Matkan, A. A., & Ahangar, A. D. (2012). Inversion of a radiative transfer model for estimaion of rice canopy chlorophyll content using a lookup-table approach. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **5**(4), 1222-1230.

12 Weiss, M., Baret, F., Myneni, R. B., Pragnère, A., & Knyazikhin, Y. (2000). Investigation of a model inversion technique to estimate canopy biophysical variables from spectral and directional reflectance data. *Agronomy* **20**(1), 3-22.

13 Richter, K., Atzberger, C., Hank, T., Mauser, W. (2012). Derivation of biophysical variables from Earth Observation data: validation and statistical measures. *JARS* **6**(1), 063557-1 - 063557-23 (Sep 04, 2012). doi:10.1117/1.JRS.6.063557.

14 Atzberger, C. (2004). Object-based retrieval of biophysical canopy variables using artificial neural nets and radiative transfer models. *Rem. sens. env.* **93**(1), 53-67.