SWAMP SCIENTIFIC REPORT - GROUP A

FIELD AND AIRBORNE SPECTROSCOPY AND ITS APPLICATION TO REMOTE SENSING OF A WETLAND ENVIRONMENT

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INTRODUCTION

The SWAMP summer school was organized in a wetland area near Obrzycko-Rzecin in Poland during the peak-growing season (July 6th-16th 2015). The summer school was aimed at using airborne hyperspectral data as well as (near-)ground data to determine Earth surface reflectance and fluorescence which play a role in supporting satellite mission design and use (e.g. FLEX) and which support multi-scale ("leaf to ecosystem") land-atmosphere exchange modelling studies.

Photosynthesis is the crucial life sustaining process of plants by which the energy from the sun in conjunction with H2O and CO_2 is assimilated into living plant matter. Carbon exchange can be measured directly through the use of gas chamber measurements, Eddy Covariance and leaf-level gas exchange measurements. However, measuring photosynthesis directly over large areas is not possible, and thus it is often estimated based on other variables which can be used to approximate it. Leaf level radiative transfer models, such as PROSPECT (Jacquemoud and Baret, 1990), have long been used to study how changes in plant structure and biochemistry influence leaf reflectance. Imaging spectroscopy data may be used to retrieve vegetation biochemical parameters, because the higher information content in hyperspectral data increases the degrees of freedom required for model inversion compared to using broadband data and simple VIs (e.g. Garbulsky et al., 2011). Vegetation stress can be detected using spectroscopic data due to the reflectance, transmittance and absorption of a leaf being influenced by the structure, water content and pigment concentration of a leaf as well as the incident irradiance (e.g. Jacquemoud and Baret, 1990). Changes occurring at an ecosystem scale, such as drought, can be detected using remote sensing, which enables us to estimate e.g. carbon sinks and sources.

According to Monteith (1972) the Net Primary Production (NPP) of an ecosystem is proportional to Absorbed Photosynthetically Active Radiation (APAR, 400-700 nm). However, to estimate NPP an estimate of Light Use Efficiency (LUE) is needed. Photochemical Reflectance Index (PRI, normalized difference ratio of bands at 531 and 570 nm) is sensitive to changes in the xanthopyll cycle (Gamon et al. 1992) which can be used to approximate LUE. Studies have shown that SIF can be used to track physiological regulation of photosynthesis and that more accurate estimates of Gross Primary Production (GPP) may be obtained by including estimates of SIF into GPP modelling approaches (e.g. Damm et al. 2009). The potential to obtain estimates of SIF using remote sensing may enhance our understanding diurnal variation of LUE and plant stresses both local and global scales (e.g. Damm et al. 2009).

The aim of our study (GROUP A) was to collect spectral data for the calibration and validation of 'homogenous' targets selected within the study area. The targets had to fulfil the following conditions: 1) Aerial extend big enough to cover at least 3X3 pixels of the airborne image data (APEX and HyPlant), these were acquired during the SWAMP summer school as well, and 2) High homogeneity. Those calibration/validation targets represented the most homogeneous, natural and accessible patchesalthough a certain amount of heterogeneity is still present within the samples. Therefore, the others scientific goals were to map this detailed scale heterogeneity of the study site at high spectral resolution, and to quantify spectroscopic uncertainties. As reflectance of an object is influenced by its spectral and structural composition, we aim to assess both. The data were collected using ASD FieldSpec spectrometer and processed using SPECCHIO. In addition, we processed data from the Rikola imaging instrument on-board an UAV platform. Field spectroscopy data were used to calibrate and validate remotely sensed data from HyPlant and APEX sensors.

During the field campaign our group mission was to measure the ground reference targets which will later be used for the validation and calibration of the airborne sensor data. Other groups missions were: B – LAI (leaf area index) measurements using SunScan Canopy Analyser, spectral imaging using the Rikola instrument onboard a UAV, spectral measurements using SpectraVista SVC spectral-radiometer; C – Canopy level Solar Induced Fluorescence (SIF) measurements using the OceanOptics HR4000 spectrometer, assisting with gas-chamber measurements; D – Leaf level SIF measurements using FluoWat spectrometer, leaf chlorophyll concentration using Apogee MC-100 Chlorophyll concentration meter, canopy level LAI and fAPAR using SunScan; E – SIF measurements from UAV platform using OceanOptics STS-VIS spectrometer. Altogether these missions resulted in a large spectral database which was stored in the online SPECCHIO database. Airborne data was collected using HyPlant and APEX sensors and Unmanned Aerial Vehicle (UAV) data using RIKOLA sensors. HyPlant and APEX sensors had sufficient spectral resolution for the SIF retrieval, but the Rikola sensor onboard the one UAV did not, whereas the STS-VIS spectrometer onboard another UAV did have the ability to measure SIF In addition, fluxes and gap probabilities were measured during the field campaign.

In this report we describe the methods of collecting and processing spectroscopy data during the field campaign. In addition to the goals specified above, it was possible to employ some spatial statistics whilest we also post-processed some of the data obtained by other groups.

STUDY SITE

The study area is located at Rzecin (52.75N, 16.29E) in Western-Poland (**Fig. 1**). The wetland is owned by Poznań University of Life Sciences. The studied peatland area covers approximately 140 ha. The vegetation is dominated by the following plant species: Sphagnum sp., Dicranum sp., Carex sp., Phragmittes communis, Typha langifolia, Vaccinium oxicoccus, Drosera rotundifolia, Potentilla palustris, Ranunculus acris, and Menyantes trifoliate (Wojterska 2001).

The annual mean air temperature and precipitation for the whole period of measurements were 8.5ºC and 526 mm, respectively. The floating peat carpet of approximately 50 cm-thick is located in the middle of the wetland (Chojnicki 2010).

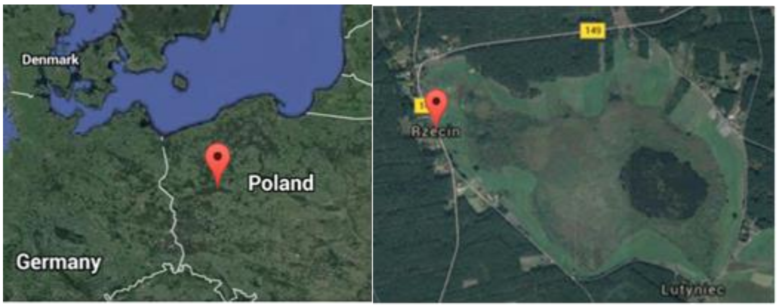

Fig. 1. Study site.

METHODOLOGY

The vegetation plot locations were selected to represent the most homogeneous patches for as many vegetation types as possible, and based on existing perpendicular elevated walkways to avoid trampling the vegetation (**Fig. 2**). Most of the plots were located on the northern side of the walkways. The tallest and most fertile vegetation were located next to the swamp edge, and the vegetation was turning into shorter and more xeric towards the centre of the swamp. In total, seven vegetation plots were measured during the field campaign, these aimed to serve as validation targets for aerial image data. In addition, three aerial image calibration targets - tarps varying in albedo, i.e. white, grey and black - were measured. Each target was measured four times, except the grey tarp which was measured three times. The tarps were laid open on an area covered by sphagnum moss to level the tarps as much as possible. Photographs were taken from the sky during the spectral measurements to document the sky conditions prevailing at the moment of the measurements. In addition, vegetation plots were photographed with a reference person holding a tape measure to quantify the height and structure of the vegetation.

The ground reference spectra were collected using ASD FieldSpec device and collected spectra were normalized using a Spectralon panel. The ASDs Sensor head was attached to a 1 m stick in order to extend the location of the FOV beyond the walkways thus also avoiding having to trampleon the vegetation in the plot area. The ground area which was covered by the ADS measurements was approximately 1 m × 2.5 m. The Spectralon plate was levelled using a spirit-level and held still by a tripod. Data were collected in a 'sweeping' mode by moving the stick with attached ASD over the target.

The sampling scheme was:

5 x ref + 30 x tgt + 5 x ref

where 'ref' denotes the Spectralon reference reading and 'tgt' is the target, with the number preceding denoting the number of measurements obtained.

Measurements were conducted when there were no visible clouds between the sun and the FOV. Field measurements were done both sides of solar noon when the suns elevation was at its highest, which was also the time at which it was planned for the aeroplanes to fly over the study area. Hemispherical-Conical Reflectance Factors were calculated using Matlab and downloaded into SPECCHIO.

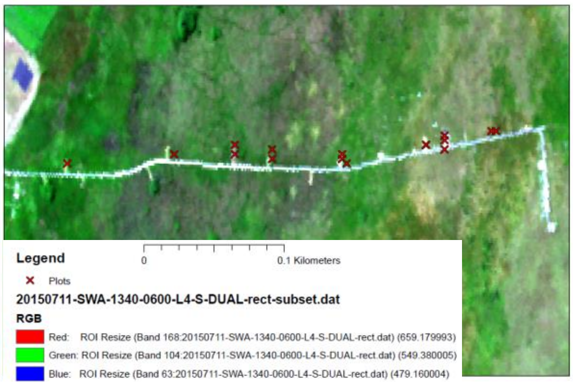

Fig. 2. Sampled plot locations.

In addition to processing and assessing the calibration/validation spectral data, we also focused on the retrieval of selected biophysical parameters. Two approaches were tested: 1) Radiative transfer modelling (RTM) using the ARTMO (www1) module (Cab, LAI and water content) (**Fig. 3**), and 2) Hybrid model for LAI and Chlorophyll retrieval (**Fig. 4, 5**).

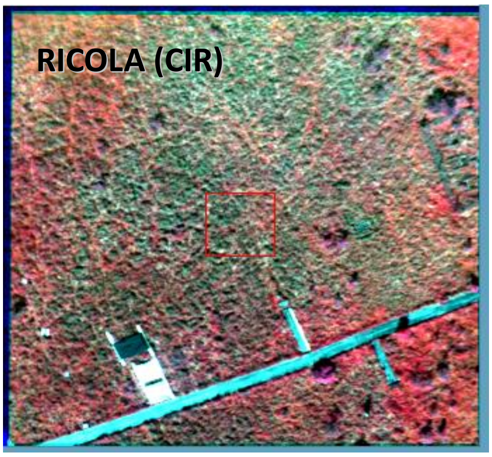

Fig. 3. Subset of the RICOLA image data used for the biophysical parameters retrieval.

Both approaches were tested on a subset of the RICOLA image data (high spatial and spectral resolution UAV based data from RIKOLA with 16 programmable bands between 500 and 900 nm, FWHM of 10 to 30 nm). For both, the same look up table (LUT) was used. This LUT was derived via parametrizing the RTM model for the RICOLA spectral resolution.

For the RTM modeling, PROSPECT4 and 4SAIL models were employed to model leaf and canopy level spectral property, respectively (**Fig. 4**). LUT based inversion was employed to model Cab, LAI and water content using acost function.

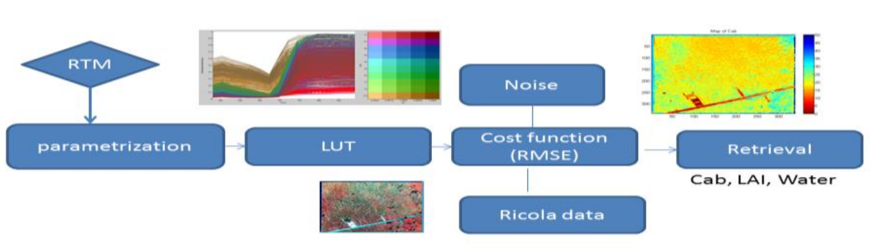

Fig. 4. Selected biophysical parameters retrieval through RTM inversion (LUT-based RTM inversion)

A hybrid model was employed to model LAI and Chlorophyll contend using a machine learning approach known as Random Forest (RF) (Breiman et al. 2001) (**Fig. 5**). RF was applied to LAI and Chlorophyll modeling across the study area. The RF method is an innovative machine learning approach that can perform multivariate non-linear regression, combining the performance of numerous regression tree algorithms to predict biophysical parameters. The RF method receives a subset of (x) input vectors, made up of the LUT. RF builds a number of regression trees (individual regression models) and averages the results. After K such trees $\{T(x)\}_1^K$ are grown, the RF regression predictor becomes:

$$\hat{f}_{rf}^{K}(x) = \frac{1}{K}\sum_{k=1}^{K} T(x)$$

More details regarding the performance and the specific characteristics of a RF model can be seen in Rodriguez-Galiano et al. (2015).

The RF model was fitted to the relation between LAI and Chlorophyll obtained from the LUT and the spectral bands of the Rikola sensor as explanatory variables. The LUT was created to simulate the reflectivity of the spectral bands of Rikola sensor for 10,000 different values of LAI and Chlorophyll content. These values were combined into a set of input feature vectors as an input to the RF algorithm. The performance of the method was evaluated using an embedded cross validation. RF models composed of 1000 trees were grown varying the number of random predictors from 1 to 16. Random Forest method within the package implemented in the R statistical software was used to build the different models (Liaw and Wiener, 2002).

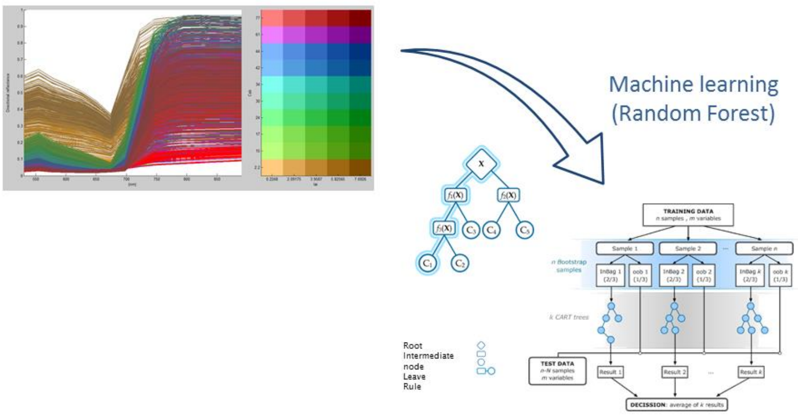

Fig. 5 Scheme of the hybrid model used for for LAI and Chlorophyll retrieval.

RESULTS

Field spectral data analysis

The smallest changes in reflectance values occurred with black reference target GT3 (std=0.02) (**Table. 1, Fig. 6**). The largest differences during the measurement rounds appeared with the plot GT8, which was dominated by high grasses. For most vegetation plots the standard deviation of spectra between the rounds was ~0.05. As the vegetation structure and species composition got more heterogeneous the standard deviation between rounds increased. For bright targets, such as GT2 and GT1, the standard deviation values were relatively large compared to coefficient of variation. As the vegetation height increased the between round variability of spectra also increased. Our results showed that smallest changes in vegetation spectra was observed in plot GT7 covered by grasses and 20% dry matter, and the largest in plot GT8 covered by high grasses and 10% dry matter.

Plot	n	Std.	CV%	Description:
GT2	4	0.05	10.22	ground white reference
GT1	3	0.05	14.03	ground grey reference
GT7	4	0.04	23.45	high grass, 20% dry matter
GT10	4	0.05	24.88	high green grass
GT4	4	0.04	25.52	vegetation, grass
GT5	4	0.05	27.49	vegetation, grass, moss (yellow), green and dry grass
GT6	4	0.05	27.90	vegetation(higher cca 50 cm), grass, green, green moss
GT9	4	0.05	30.57	very high grass, wet, growing in water
GT3	4	0.02	37.69	ground black reference
GT8	4	0.08	49.38	high grass, 10% dry matter

Table 1. Field plot description and results. Plot = plot ID, n = number of measurements, Std. = standard deviation between different measurements rounds, CV% = Coefficient of variation.

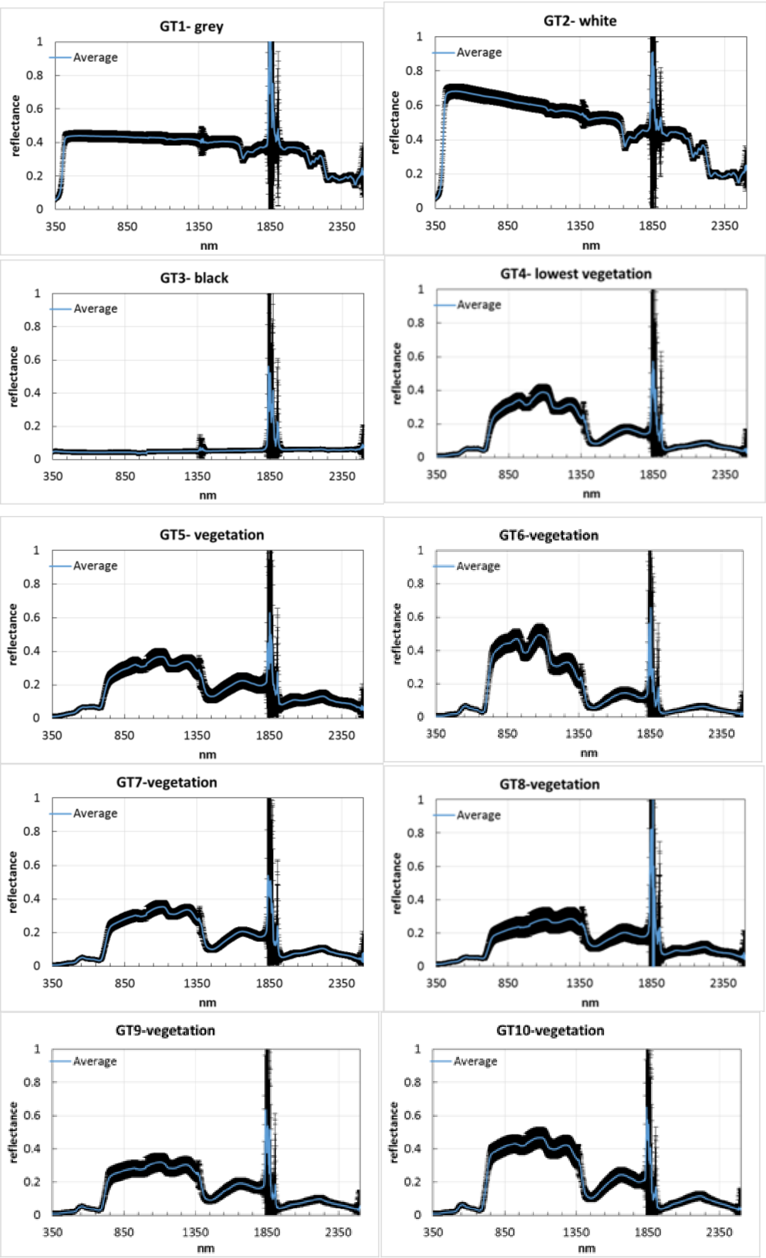

Fig. 6. The mean and standard deviation of the reference tarps a-c and vegetation plots d-j: **a)** white, **b)** grey, **c)** black, **d)** GT4, **e)** GT5, **f)** GT6, **g)** GT7, **h)** GT8, **i)** GT9, **j)** GT10.

Biophysical parameters retrieval

Employing the RTM model it was possible to model the Cab content successfully (Fig. 7). The retrieved values were within the range that was measured in the field by a different group. In addition, the CV values are mainly below 20%. For the LAI, for most of the area the CV values were below 10%, however, some parts showed very high CV values (80%) (Fig. 8, right panel). The value range was too high when compared to the field measurements. This shows that the model would need a further fine tuning. The worse results were obtained for the water content modelling (Fig. 9), the CV values are overall higher than 60%.

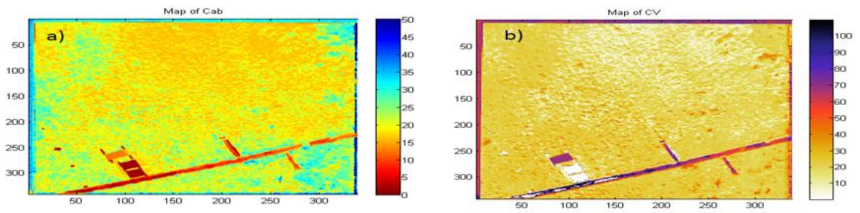

Fig. 7. Cab retrieval employing the RTM.

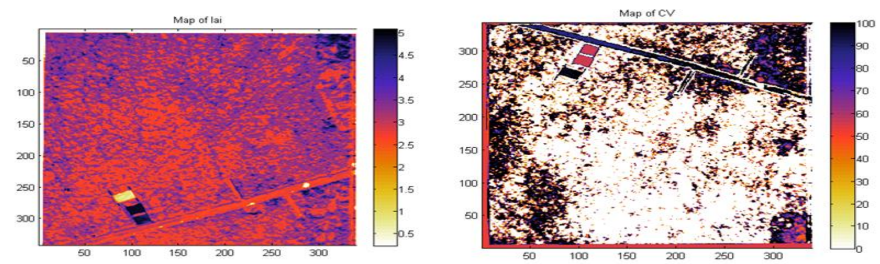

Fig. 8. LAI retrieval employing the RTM.

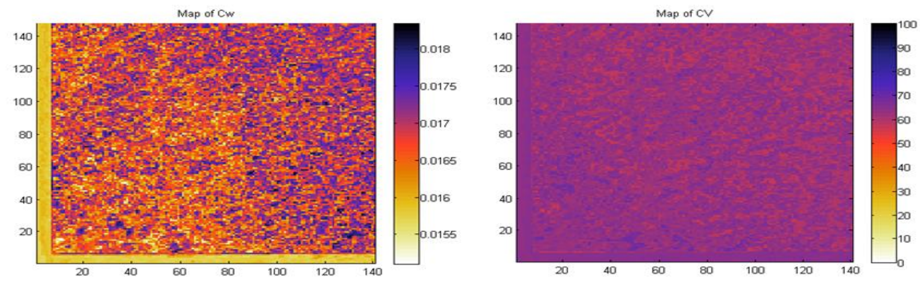

Fig. 9 Water content retrieval employing the RTM.

Two different models of LAI and Chlorophyll were built on the basis of the LUT. The percentage of variation (pseudo-R2) explained by the LAI and Chlorophyll models were equal to 0.73 and 0.96 µg/cm^{-2}, and the root mean square error equal to 1.02 and 4.62 µg/c^{m-}2 respectively.

Z komentarzem [1]: LAI is unitless as it is a ratio of m2 / m2. In literature µg/cm^{-2} is used.

Z komentarzem [VRG2]: Veronika, what are the units for LAI and Cab

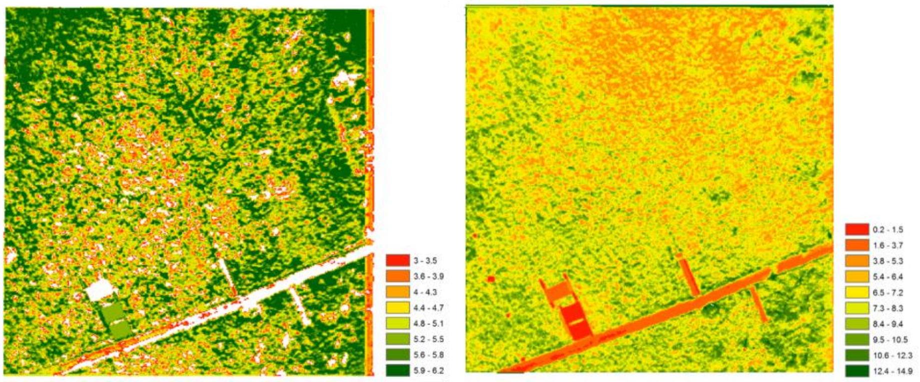

Figure 10 Predicted LAI (left) and Chlorophyll (right).

DISCUSSION

The uncertainties related to spectroscopy need to be understood before meaningful inference can be made. A non-exhaustive list include lens aberration, saturation of the signal, degradation of the detectors, atmospheric and hydrometeorological parameters (changes in moisture, cloud coverage, temperature and pressure), calibration wavelengths, directional distribution of incoming irradiation etc.

Some of the variations were due to different people taking measurements at different times of the same location. We could not make sure the exact same spots was measured at every round. The angle and height of the stick where the ASD head was attached changed slightly due to the varying heights of individuals taking the measurements. As the day progressed the sun angle changed, which we could not take into account while we were measuring. We tried to reduce the effect of background or soil/water influence on the spectra by selecting areas which have fewer gaps between vegetation. Yet the influence of shadowing by taller plants cannot be neglected.

In addition, we made an attempt to retrieve selected biophysical parameters using the RICOLA data. The Cab retrieval was the most reliable while modelling the water content was the most problematic. The Ricola data don't cover the optimal spectral range (500-900 nm), as for modeling the water content the longer wavelengths would have been more beneficial. However, the RICOLA data seems to be promising for modelling the chlorophyll as well as LAI (after some fine tuning).

Systematic errors may be due to the Spectralon panel which was moved between every vegetation plot. The tarps were probably the worst to measure, because they were not leveled at all due to understory vegetation. In addition, we could not take into account changes in direct and diffuse radiation. Small clouds might have influenced our results. Cirrus clouds were probably avoided due to variable illumination conditions. However, our results demonstrated that the repeatability of the spectral measurements was relatively good although slight changes might have occurred during the measurements.

Any future study could look at how the implementation of various machine-learning algorithms could be refined to improve retrievals of canopy level biochemical and biophysical variables. A Bayesian regularisation approach could be implemented with prior information from other datasets.

CONCLUSION

We succeeded in completing our objective to collect ground reference data for the calibration and validation of the airborne surveys. The error bars of the spectra describe the sum of errors introduced by different error sources during the day, and thus can be used to quantify the relative heterogeneity of the different vegetation types. The different error sources were discussed which could have contributed to the variation in the datasets.

Multivariate non-parametric models based on the LUT and the UAV Rikola sensor were able to predict LAI and Chlorophyll accurately (pseudo R2 equal to 0.73 and 0.96, respectively; RMSE equal to 1.02 days and 4.69µg/c^{m-}2, respectively).

Z komentarzem [VRG3]: Veronika, what are the units for this?

ACKNOWLEDGEMENTS

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