INVERSION OF THE PROSAIL MODEL FROM UAV DATA

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ABSTRACT

In this paper, we present an innovative workflow for retrieving biophysical traits of vegetation by means of inverting the radiative transfer model PROSAIL from UAV borne hyperspectral data. The approach makes use of spectral images acquired with a Fabry-Perot interferometer in the visible and near infrared spectral range. Even of the reduced spatial coverage of UAV acquisition, the high spatial resolution of such images makes model inversion computationally highly demanding. To overcome this, we made use of a machine learning method. Firstly, we generated look up tables by means of model forward runs based on variating model parameters according to prior knowledge. Random forests were then trained and applied to radiometrically calibrated UAV borne images. This allowed to retrieve model parameters for the area of interest (AOI). The approach showed to be computationally efficient and usable for ecosystems with high spatial variability.

***Index Terms*—** UAV, PROSAIL, model inversion, machine learning, ecosystem traits

1. INTRODUCTION

In the recent years many low-cost and lightweight multispectral sensors became available in the market. These instruments favored the development of vegetation indices (VI) approaches for qualitative assessment of vegetation properties [1][2]. Beside such sensors, a number of UAV carryable hyperspectral instruments are being used by the scientific community. Such sensors are more sophisticated and require proper acquisition and calibration. On the other side, hyperspectral data are a powerful tool for investigating quantitatively vegetation properties. In fact, such data can be used for inverting radiative transfer models. Calibrated model parameters can be then assimilated to ecosystem traits. This offers unforeseen possibilities for ecological analysis at very high spatial resolution.

2. METHODS

2.1. The study area

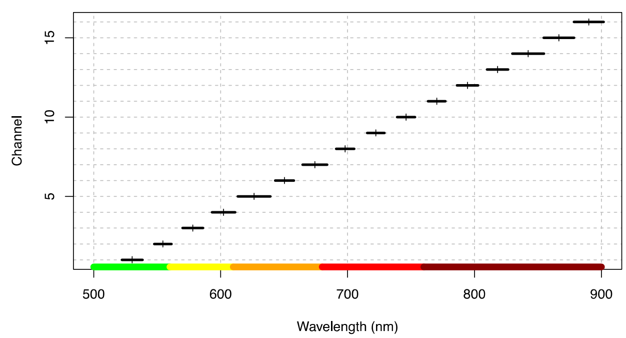

Fig. 1: channels and full width at half maximum for the adopted acquisition modus of the Fabry Perot interferometer.

The area of interest is located in an alpine valley (46.68° N, 10.59° E). The ecosystem is a dry pasture with sparse shrubs. Patches are dominated by grasses and others are dominated by herbs [3]. This was selected because of its very high spatial complexity.

2.1. Image pre-processing

The method described in this paper was applied to data collected during an acquisition campaign from 21 August 2015. The Fabry Perot interferometer (Rikola Ltd.) was mounted on a UAV and stabilized by means of a gimbal to minimize changes of viewing geometry during the acquisition of spectral bands. The sensor was programmed to acquire equidistanced bands (Fig. 1). An automatic flight with constant speed (1 m/s) and height (70 m) was conducted over the AOI. The sensor was activated by an intervalometer (3 seconds interval).

Because of the sensor technology spectral bands are acquired sequentially therefore - to produce data cubes - we had to perform a band to band match as described in [4] and [5]. Quality of matched data cubes was then assessed based on total number of black pixels. Cubes with bad matching were excluded. The bands were then mosaicked and orthorectified. Shadows were classified by means of a 2 classes kmeans in the band number 14. We made use of infrared because in this part of spectrum differences between shadows and lights are more relevant. We masked such areas. To overcome to issues with directional observation at the margins of the AOI, we removed pixels obtained by the composition of less that 5 single images. Ground spatial resolution was finally reduced to 0.5 m.

2.2. Radiometric calibration

We performed a radiometrical calibration of mosaics by using near nadiral acquisition of black and white ground reference panels. The reference material used was "Odissey64" (Kayospruce Ltd.). The spectral properties of the material were characterized in controlled conditions with a spectrometer (hr1024i SVC Ltd.). Mean reflectance in the range 500 to 900 nm for the white panel was 0.728 (sd 0.011) and for the black panel 0.0378 (sd 0.001). For the calibration of the mosaics we applied the empirical line method.

2.3. Model forward runs

Models runs were executed making use of Prosail 5b [6]. Leaf angle distribution was assumed to be spherical. The angle of observation was fixed to nadiral. Sun geometry was set as from the time and location of the acquisitions. We decided to focus on model parameters that are assimilable to ecosystem traits and are measurable in the field: chlorophyll content (range 10-40 µg/cm²) and Leaf Area Index (0.1 to 5 m²/m²). Other parameters were fixed to standard values. The chosen parameters were varied randomly and model was run for 100000 times. Data were convoluted to the spectral response functions of the Fabry Perot interferometer. We added random noise to the modelled spectra. In this way, we made our approach capable to account for noise in the field measurements.

2.3. Model inversion

For inverting the model, we made use of Random Forests [7]. This was used as an ensemble method for regression that is based on the uncontrolled development of decision trees (n = 200). We opted for this method because of its demonstrated efficiency with large data sets.

6. RESULTS

6.1 Sensitivity to model parameters

A "parameter at time" sensitivity analyses showed that spectra are affected differently by the two model parameters that we opted to calibrate. In fact, leaf area index (Fig. 1a) seems to be a key for the whole spectral range but still more important in the infrared region. On the other side, chlorophyll content (Fig 1b) affects more the difference between the green and red regions. We assume therefore that effects of the 2 parameters can be distinguished in the inversion model process.

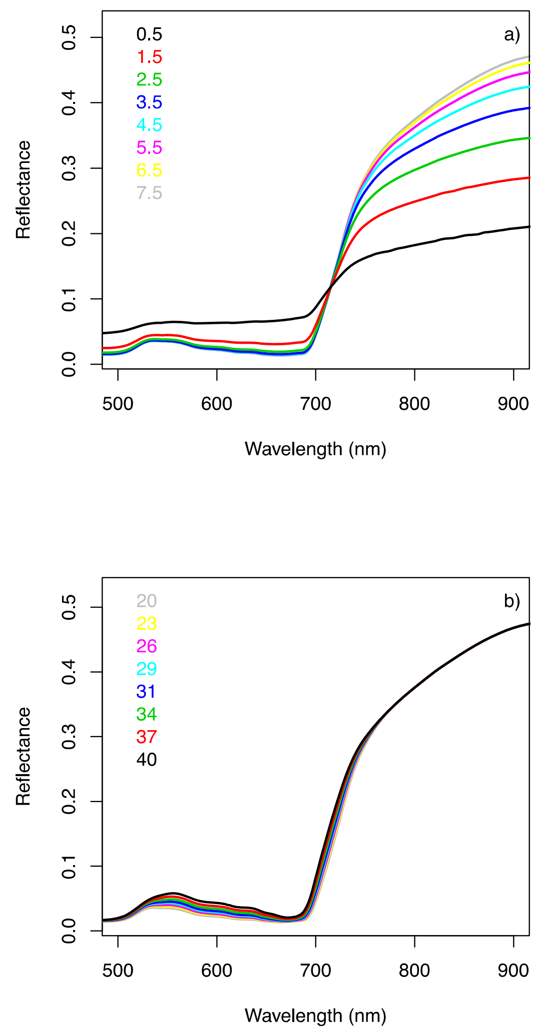

Fig. 2: sensitivity of model output to a) leaf area index and b) Chlorophyll content model parameters.

6.2 Maps of ecosystem traits

We found that spatial patterns of LAI parameter (Fig. 3a) correspond to field observations. Range of measured LAI of herbaceous patches at the study site by means of laboratory analyses was 0.79-2.89 m^2/m^2. In our inversion approach such values are exceeded just by shrubs. Chlorophyll content values (Fig 3b) were consistent with literature for this vegetation type.

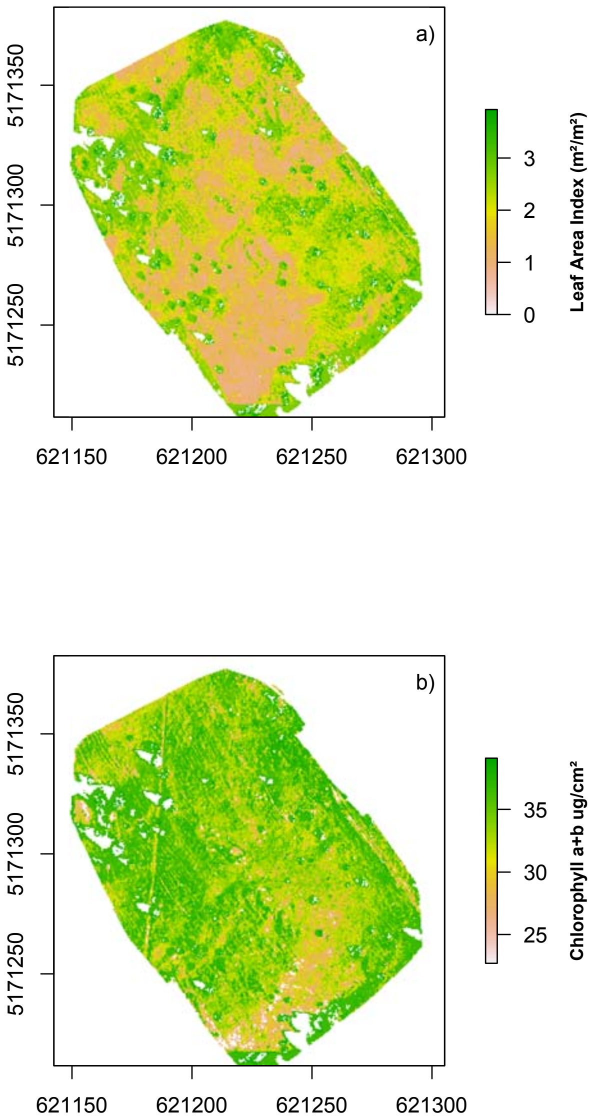

Fig. 3: maps of inverted a) LAI and b) Chlorophyll content model parameters.

5. CONCLUSIONS

UAV borne imaging spectrometry can provide very high spatial resolution data. Such data have to be calibrated with ground references because of scale affinity. Calibrated mosaics can be used for inverting radiative transfer model allowing for mapping ecosystem traits with very high spatial resolution. Still, classical methods are computationally intensive. Our approach is capable efficiently to provide quantitative information overcoming the limitation of vegetation indexes. Our first results showed that model retrievals of herbaceous vegetation are consistent with the range of ground measurements and literature values. We conclude that UAV measurements have a potential mapping ecosystem traits at landscape level over vegetation with complex patterns.

11. REFERENCES

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