RETRIEVAL OF VEGETATION BIOCHEMICALS USING A RADIATIVE TRANSFER MODEL AND HYPERSPECTRAL DATA

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ABSTRACT:

Accurate quantitative estimation of vegetation biochemical characteristics is necessary for a large variety of agricultural and ecological applications. The advent of hyperspectral remote sensing has offered possibilities for measuring specific vegetation variables that were difficult to measure using conventional multi-spectral sensors. In this study, the potential of biophysical modelling to predict leaf and canopy chlorophyll contents in a heterogeneous grassland is investigated. The well-known PROSAIL model was inverted with HyMap measurements by means of a look-up table (LUT). HyMap images along with simultaneous in situ measurements of chlorophyll content were acquired over a National Park. We tested the impact of using multiple solutions and spectral sub-setting on parameter retrieval. To assess the performance of the model inversion, the RMSE and R^2 between independent in situ measurements and estimated parameters were used. The results of the study demonstrated that inversion of the PROSAIL model yield higher accuracies for Canopy chlorophyll content, in comparison to Leaf chlorophyll content (R^2=0.84, RMSE=0.24). Further a careful selection of spectral subset, which comprised the development of a new method to subset the spectral data, proved to contain sufficient information for a successful model inversion. Consequently, it increased the estimation accuracy of investigated parameters (R^2=0.87, RMSE=0.22). Our results confirm the potential of model inversion for estimating vegetation biochemical parameters using hyperspectral measurements.

1. INTRODUCTION

The spatial and temporal distribution of vegetation biochemical and biophysical variables are important inputs into models quantifying the exchange of energy and matter between the land surface and the atmosphere. Among the many vegetation characteristics, leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) are of prime importance. Leaf chlorophyll content and canopy chlorophyll content (the latter defined here as the product of LAI and leaf chlorophyll content) contribute to verifying vegetation physiological status and health, and have been found useful for detecting vegetation stress, photosynthetic capacity, and productivity (Boegh et al., 2002; Carter, 1994).

The physical approach for estimating vegetation parameters from remotely sensed data, involves using radiative transfer models. This approach assumes that the radiative transfer model accurately describes the spectral variation of canopy reflectance, as a function of canopy, leaf and soil background characteristics, using physical laws (Goel, 1989; Meroni et al., 2004). As radiative transfer models are able to explain the transfer and interaction of radiation inside the canopy based on physical laws, they offer an explicit connection between the vegetation biophysical and biochemical variables and the canopy reflectance (Houborg et al., 2007). To actually use physically based models for retrieving vegetation characteristics from observed reflectance data, they must be inverted (Kimes et al., 1998). A drawback in using physically based models is the ill-posed nature of model inversion (Atzberger, 2004; Combal et al., 2002), meaning that the inverse solution is not always unique as various combinations of canopy parameters may yield almost similar spectra (Weiss and Baret, 1999). To overcome this problem, some restriction of the inverse problem may be required to constrain the inversion process. This involves the use of prior knowledge about model parameters (Combal et al., 2002; Lavergne et al., 2007).

Significant efforts to estimate and quantify vegetation properties using radiative transfer models have been carried out in the last two decades. Despite these efforts, literature reveals that studies on heterogeneous grasslands with combinations of different grass species and the use of hyperspectral measurements are rare. The main objective of this paper is to estimate and predict canopy and leaf chlorophyll content by inverting the canopy radiative transfer model PROSAIL (Jacquemoud and Baret, 1990; Verhoef, 1984; Verhoef, 1985). The aptness of the methods is analyzed in terms of prediction accuracy for estimating leaf and canopy chlorophyll content.

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2. MATERIALS

2.1 Study area and sampling

The study site is located in a National Park in Italy (latitude 41°52' to 42°14'N, longitude 13°50' to 13°14'E). The park covers an area of 74.095 ha and extends into the southern part of Abruzzo, at a distance of 40 km from the Adriatic Sea. The region is situated in the massifs of the Apennines. The flora of the park includes more than 1800 plant species, which approximately constitute one third of the entire flora in Italy. A total of 45 plots (30 m by 30 m) were selected. For each plot, the relevant biophysical and biochemical parameters were measured within few randomly selected subplots. In each plot the species varied in terms of leaf shape, size and the amount of leaves.

2.2 Vegetation parameter measurements

A SPAD-502 Leaf Chlorophyll Meter was used to assess leaf chlorophyll content. A total of 150 leaves were randomly selected in each plot representing the dominant species and their SPAD readings were recorded. From the 150 individual SPAD measurements, the average was calculated. These averaged SPAD readings were converted into leaf chlorophyll contents [µg cm^{-2}] by means of an empirical calibration function provided by (Markwell et al. 1995). The total canopy chlorophyll content (CCC) [g m^{-2}] for each plot then have been obtained by multiplying the leaf chlorophyll content with the corresponding leaf area index

In each plot, leaf area index was measured using the Plant Canopy Analyzer LAI-2000 (LICOR Inc., Lincoln, NE, USA). To prevent direct sunlight on the sensor, samples of below- and above-canopy radiation were made with the sun behind the operator and using a view restrictor of 45°. Table 1 reports summery statistics for some of the measured variables of the plots.

Measured variables	STDV	Min	Mean	Max
SPAD (unit-less)	3.7	24.2	32.7	41.0
Leaf chlorophyll (µg cm^{-2})	4.7	18.9	28.7	40.9
Canopy chlorophyll (g m^{-2})	0.56	0.21	0.86	2.3
LAI (m^2 m^{-2})	1.59	0.72	2.87	7.54

Table 1. Summary statistics for some measured variables of sample plots.

2.3 Hyperspectral images

HyMap images of the study area were acquired by DLR, Germany’s Aerospace Research Centre and Space Agency. The sensor contained 126 wavelengths, operating over the spectral range of 436 nm to 2485 nm. The spatial resolution of the data was 4 m. The data were collected in four image strips, each covering an area of about 40 km by 2.3 km. The image acquisition was close to solar noon. The image strips were atmospherically and geometrically corrected by DLR. A 7 by 7 pixel window centred around the central position of a plot was used for collection of grass spectra from each sample plot and its average spectrum was calculated.

3. METHODS

3.1 PROSAIL & Inversion

The commonly used PROSAIL radiative transfer model which is a combination of the SAILH canopy reflectance model (Verhoef, 1984; Verhoef, 1985) and the PROSPECT leaf optical properties model (Fourty et al., 1996; Jacquemoud and Baret, 1990; Jacquemoud et al., 1996) was selected for canopy parameter retrieval. The PROSPECT model calculates the leaf hemispherical transmittance and reflectance as a function of four input parameters: the leaf structural parameter N (unitless); the leaf chlorophyll a + b concentration LCC (µg cm^{-2}); the dry matter content Cm (g cm^{-2}); and the equivalent water thickness Cw (g cm^{-2}). The SAILH model, apart from the leaf reflectance and transmittance, requires eight input parameters to simulate the top-of-canopy bidirectional reflectance. These are sun zenith angle, ts (deg); sensor viewing angle, to (deg); relative azimuth angle between sensor and sun, phi (deg); fraction of diffuse incoming solar radiation, skyl; background reflectance (soil reflectance) for each wavelength, rsl; LAI (m^2 m^{-2}); average leaf inclination angle, ALA (deg); and the hot spot size parameter, hot (m m^{-1}). To account for the changes induced by moisture and roughness in soil brightness, we used a soil brightness parameter, scale (Atzberger et al., 2003). Sensor viewing angle, azimuth angle, sun zenith angle and fraction of diffuse incoming solar radiation were fixed.

The inversion of PROSAIL radiative transfer model was considered by using a look-up table (LUT). To build the LUT, 100,000 parameter combinations were randomly generated and used in the forward calculation of the PROSAIL model. The ranges (minimum and maximum) for each of the eight “free” model parameters are reported in Table 2. The maximum and minimum values of LAI, LCC and ALA were fixed based on prior knowledge from the field data collection (Combal et al., 2003; Darvishzadeh et al., 2008). To find the solution to the inverse problem for a given canopy spectra, for each modelled reflectance spectra of the LUT the root mean square error between measured and modelled spectra (RMSEr) was calculated.

Parameter	Min	Max
Leaf area index	0	8
Mean leaf inclination angle	40	70
Leaf chlorophyll content	15	45
Leaf structural parameter	1.5	1.9
Dry matter content	0.005	0.010
Equivalent water thickness	0.01	0.02
Hot spot size	0.05	0.10
Soil brightness	0.5	1.5

Table 2. Specific ranges for eight input parameters used for generating the LUT.

4. RESULTS

To find the solution to the inverse problem, the LUT is sorted according to the cost function and the set of variables providing the minimum RMSE is considered as the solution. Figure 1 illustrates measured and simulated canopy reflectance spectra found in this way for two plots with contrasting LAI values.

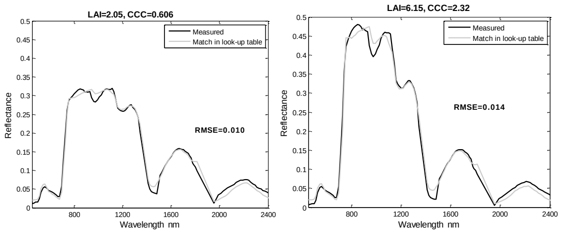

Figure 1. Measured and simulated canopy reflectance spectra of two sample plots.

Generally the simulated reflectances were in relatively good agreement with the measured reflectances for canopies with different LAI values. A more concise analysis reveals that most spectral bands were modelled with average absolute error (AAE) lower than 0.02 reflectance units. As Figure 2 shows the AAE in some regions is relatively high (greater than 0.02), especially close to the water vapour absorption regions (1135 nm to 1400 nm, and 1820 nm to 1940 nm). We considered the bands with an AAE greater or equal to 0.02 as wavelengths being either poorly modelled or poorly measured (Darvishzadeh et al., 2008).

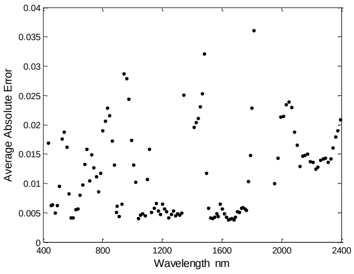

Figure 2. The average absolute error between best-fit and the measured HyMap reflectance.

The relation between the measured and estimated grass canopy chlorophyll content based on the smallest RMSE criterion is demonstrated in Figure 3.

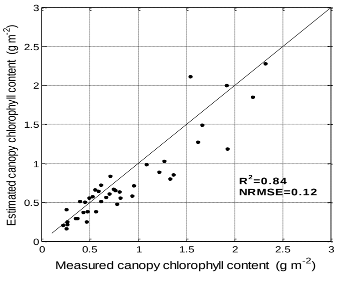

Figure 3. Estimated versus measured canopy chlorophyll using the PROSAIL model and the minimum RMSE criterion in the LUT search.

We also evaluated the retrieval accuracy if multiple solutions are used. Table 3 compares the "multiple solutions" with the "best-fit" LUT solutions. This demonstrates how different solutions affect the accuracy of the estimated variables.

No. of Solu.	Stat. Param	LCC (μg cm^{-2})			CCC (g m^{-2})		
		R^2	RMSE	nRMS	R^2	RMSE	nRMS
Best spectra	/	0.35	3.8	0.17	0.84	0.24	0.12
First 10	Median	0.36	3.8	0.17	0.84	0.24	0.12
	Mean	0.36	3.7	0.17	0.85	0.23	0.11
First 100	Median	0.39	3.1	0.14	0.81	0.25	0.12
	Mean	0.40	3.1	0.14	0.82	0.24	0.11

Table 3. R^2, RMSE and normalized RMSE between measured and estimated leaf and canopy chlorophyll content from PROSAIL inversion.

An appropriate band selection is known to improve radiative transfer model inversion and prevents bias in the estimation of the variables of interest (Schlerf and Atzberger, 2006). Therefore, to account for band selection the inversion of the model was also tested with wavelengths that had an AAE smaller than 0.02. We considered bands with an AAE greater or equal to 0.02 as wavelengths with high errors (Figure 2). These bands were systematically excluded in the inversion process, and each time the AAE between the measured and best-fit reflectance spectra was re-calculated until all remaining wavelengths had an AAE smaller than 0.02. The elimination of wavelengths stopped after 19 iterations. The remaining wavebands (n=107) are called subset II and was used in the inversion procedure.

The assignment of the spectral subset II in the estimation of grass chlorophyll was again evaluated on the basis of the R^2 and the normalized RMSE between the measured and estimated variables. The results showed that, after removing the wavelengths with high AAE (AAE≥0.02), the relationships between measured and estimated leaf and canopy chlorophyll content were considerably improved (Table 4).

Spectral sampling set	Stat. Param	LCC (μg cm^{-2})			CCC (g m^{-2})		
Using all bands (n=126)		R^2	RMSE	nRMS	R^2	RMSE	nRMS
	Best fit	0.35	3.8	0.17	0.84	0.24	0.12
	median	0.36	3.8	0.17	0.84	0.24	0.12
	mean	0.36	3.7	0.17	0.85	0.23	0.11
Subset II (n=107)	Best fit	0.37	3.7	0.17	0.84	0.25	0.12
	median	0.38	3.4	0.15	0.87	0.23	0.11
	mean	0.39	3.2	0.14	0.87	0.22	0.10

Table 4. R^2, RMSE and normalized RMSE between measured and estimated leaf and canopy chlorophyll content from PROSAIL inversion using subset II.

Overall, the estimation accuracies between measured and estimated leaf and canopy chlorophyll content improved using the spectral subset (Table 4). This reflects the danger with existing bands that may contain (excessively) high noise levels and/or are poorly modelled by PROSAIL.

5. CONCLUSION& DISCUSSION

The results of the study demonstrated that inversion of the PROSAIL model yield higher accuracies for Canopy chlorophyll content, in comparison to Leaf chlorophyll content. The inclusion of canopy chlorophyll content allows us to assess whether canopy reflectance is a better predictor of leaf or canopy chlorophyll content. The relationships between measured and estimated leaf chlorophyll content were poor in all inversion processes which confirms other studies revealing similar difficulties in estimating leaf chlorophyll (Baret and Jacquemoud, 1994). This is also in line with previous studies that have demonstrated poor signal propagation from leaf to canopy scale. A careful selection of spectral subset, which comprised the development of a new method to subset the spectral data, proved to contain sufficient information for a successful model inversion. By eliminating wavelength having a high AAE (subset II), we eliminated noisy/badly modelled wavelengths. Consequently, it increased the estimation accuracy of investigated parameters (R2=0.87, RMSE=0.22). Although our results confirm the potential of model inversion for estimating vegetation biochemical parameters using hyperspectral measurements, its applicability to heterogeneous grasslands requires further experiments and validation work using different hyperspectral data sets.

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