ASSESSING THE INFLUENCE OF SPECTRAL BAND CONFIGURATION ON AUTOMATED RADIATIVE TRANSFER MODEL INVERSION

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ABSTRACT:

The success of radiative transfer model (RTM) inversion strongly depends on various factors, including the choice of a suited radiative transfer model, the followed inversion strategy, and the band configuration of the remote sensing system. Current study aims at addressing the latter, by investigating the influence of band configuration on the automated CRASh RTM inversion approach (Dorigo et al., 2008) which is based on PROSPECT and SAILh. The tested band combinations included the configurations of two commonly used hyperspectral (HyMap, CHRIS) and three multispectral (Landsat ETM+, SPOT HRV, Quickbird) sensors which, apart from the number of bands, greatly differ in the covered spectral range. For the comparison study, reflectance data were taken with an ASD Fieldspec PRO FR field spectrometer at various intensively managed grasslands in southern Germany, and measured spectra were resampled to the five studied band configurations. Leaf area index, leaf water content, and leaf dry matter content were determined for validation purposes.

Most accurate inversion results were obtained for the full-range, hyperspectral HyMap configuration, shortly followed by the multispectral Landsat ETM+ configuration and at some distance by the SPOT configuration. For the studied variables, CHRIS and Quickbird configurations provided clearly less accurate results. The obtained results indicate that an even distribution of nearly uncorrelated bands across the entire solar-reflective domain contributes more heavily to a robust inversion than a high absolute number of bands in strongly correlating waveband regions, such as provided by CHRIS. The inclusion of SWIR bands led to regularization of the leaf water retrievals and hence to stabilization of the complete inversion process. The results in this study obtained from measured data may provide an important contribution to sensor development studies, which are often based only on simulated data.

1. INTRODUCTION

In recent years, radiative transfer model (RTM) inversion has established itself as a vigorous alternative for the characterization of vegetation canopies and found its way into the generation of several operationally generated satellite-based products (e.g. Bacour et al, 2006; Knyazikhin et al, 1999). Various factors are responsible for the success of model inversion. First of all, the choice of an adequate model should be considered. The chosen model should be able to accurately describe the reflectance of the canopy of interest on the one hand, and not being too complex or requiring too many input variables on the other, as the latter may hinder the invertibility of the model. Second, an inversion technique should be chosen that is adapted to the requirements regarding processing speed, the biophysical and biochemical variables to be provided, and the available *a priori* knowledge. Several techniques are available that all have their advantages and disadvantages in specific situations (Dorigo et al., 2007). Adequate parametrization of model parameters and constraints during model inversion may help to prevent ill-posed solutions and render the retrieval more stable (Combal et al., 2002). Finally, the configuration of the remote sensing system itself or

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the choice of a subset of bands made by the algorithm or user determine to a high agree the output accuracy of model inversion.

The way in which sensor specifications influence the results are various. The number of bands and the distribution of bands across the spectrum primarily affect the amount of available spectral information and, hence, the well-determinedness of the inversion problem. Most independent spectral information is obtained when the available bands are located at positions in the spectrum that are least correlated. In addition, bands should be positioned in wavelength domains that are sensitive to changes in the variables of interest. For example, for the detection of canopy water at least one band should be situated at a wavelength of 970 nm or more (Jacquemoud and Baret, 1990). Band width affects variable retrievals in two ways: on the one hand narrow bands are better able to describe distinctive absorption features such as water absorption bands or features caused by carbon based absorbing materials such as cellulose and starch (Fourty and Baret, 1997). On the other hand, the use of narrow bands may lead to a loss of the signal-to-noise ratio and therefore may require a better description of the spectral uncertainty.

In the preparation of future satellite missions several studies already addressed the importance of sensor configuration on the retrievability of canopy variables by radiative transfer model inversion (e.g. Verhoef, 2007). Nevertheless, such studies are generally based on simulated data and theoretic sensor properties. The current study can be viewed as complementary to such theoretical studies and aims at assessing the influence of the band configurations of five operational sensors on radiative transfer model inversion. The tested band combinations included the configurations of two commonly used hyperspectral (HyMap, CHRIS) and three multispectral (Landsat ETM+, SPOT HRV, Quickbird) sensors which, apart from the number of bands, greatly differ in the covered spectral range.

2. METHODS

2.1 Test site and ground validation measurements

The study was performed in the catchment of Lake Waging-Taching which is situated in the foreland of the Bavarian Alps, close to Salzburg. Within the study area, three agricultural fields (i.e. two intensively managed meadows and one intensively used pasture) were selected for detailed anaylsis. The three grasslands were sampled by biometric spectroradiometric field measurements at June 30 and August 4, 2003. At both dates, the first meadow was characterized by a fully developed canopy, while the second meadow had been recently cut and hence contained a considerable amount of dry material. During both events the pasture was characterized by alternating densely grazed and ungrazed vegetation patches. Five to seven sample plots at each field were selected on a stratified basis. At each sample plot an area of 1×1 m^2 was selected for further analysis. Leaf fresh weight was determined by harvesting the total above ground biomass of the square meter while leaf dry weight was determined after oven-drying the sample at 70°C for 36 hours. The total amount of water was calculated by the difference between fresh and dry leaf weight. Leaf area index (LAI) of the entire above ground vegetation of each sample was determined by applying a previously established linear relationship between scanned leaf area and wet biomass (see Dorigo (2008) for details). Leaf dry matter content (*Cdm;* $g\cdot cm^{-2}$) and leaf water content (*Cw;* $g\cdot cm^{-2}$) were calculated by dividing leaf dry weight and the total amount of water, respectively, by the LAI (Ceccato et al., 2001).

2.2 Field spectrometer measurements

Spectral properties of each single plot were measured exactly on the location where subsequently the biometric sampling would take place. This enabled a direct comparison between the structural and chemical composition of the plots and their spectral properties. Per sample plot, ten spectroradiometric measurements were taken using a portable Fieldspec PRO FR spectrometer (Analytical Spectral Devices, Inc.). The radiance measurements were directly converted into reflectance by taking a Spectralon™ panel as a white reference. The single spectra were corrected for the spectral properties of the applied Spectralon panel, deviations of the white reference off the 100 % reflectance line and spectral jumps between the VNIR and SWIR1 detector (Dorigo et al., 2006). Subsequently, the average reflectance per sample plot was calculated. Due to technical problems with the spectrometer, only 29 plots of the initially 34 sample plots could be used for further analysis.

To study the influence of spectral band configuration on the performance of radiative transfer model inversion, the average ASD Fieldspec spectrum of each plot was resampled to the spectral characteristics (including band position and spectral response functions) of five commonly used sensors. These included the configurations of two commonly used hyperspectral (HyMap, CHRIS) and three multispectral (Landsat ETM+, SPOT HRVIR, Quickbird) sensors which, apart from the number of bands, greatly differed in the covered spectral range (Table 1).

Table 1. Spectral configuration of HyMap 2003, CHRIS Mode5, Landsat ETM, Quickbird, and SPOT HRG.

Sensor	Spectral range [µm]	Number of bands	Band position (Full width half maximum [nm])
Quickbird	0.45 – 0.90	4	485 (70), 560 (80), 660 (60), 830 (140)
SPOT HRVIR	0.50 – 1.75	4	545 (90), 645 (70), 835 (110), 1665 (170)
Landsat 7 ETM	0.44 – 2.36	6	478 (71), 570 (80), 662 (61), 874 (126), 1648 (200), 2224 (280)
CHRIS Mode 5	0.44 – 1.04	37	Contiguous at 6 - 30 nm distance (6-47)
HyMap 2003	0.44 – 2.48	126	Contiguous at 13 - 17 nm distance (11-22)

2.3 Radiative transfer model inversion

Radiative transfer model (RTM) inversion was based on a modified version of the CRASh approach (Dorigo, 2008, Dorigo et al., 2007). CRASh is a fully automated image-based approach for the simultaneous inversion of the leaf optical model PROSPECT (Jacquemoud and Baret, 1990; Fourty et al., 1996) and the 1-D turbid medium canopy structure model SAILh (Verhoef, 1984). Input to CRASh is atmospherically corrected top-of-canopy reflectance which is first classified according to a rough land cover classification scheme. The land cover classification optimizes the retrieval procedure for a restricted variable range and allows the calculation of a variance-covariance matrix of the wave bands as an indication of spectral uncertainty. The latter is especially important in the case of hyperspectral data where a high correlation exists between the reflectance values in the various spectral bands. Model inversion in CRASh is based on lookup tables (LUTs) which are automatically generated for each land cover class while taking into account present illumination and observation geometry and local background reflectance.

In contrast to the full version of CRASh, which also optimizes in the variable space, for this study minimization occurred only in the spectral domain. Two cost functions were tested. The first cost function was based on the maximum likelihood concept and considers the uncertainty in each band independent from that in the other bands:

$$\chi^2 = \sum_{i=1}^{n} \frac{(R^i_{meas} - R^i_{sim})^2}{\sigma_i^2} \qquad (1)$$

R^i_{meas} and R^i_{sim} are the measured and simulated reflectance in band *i*, respectively, σ_i^2 is the variance in band *i*, and *n* is the number of bands. The second cost function also considered the covariance between spectral bands:

$$\chi^2 = (R_{meas} - R_{sim})^T \cdot C^{-1} \cdot (R_{meas} - R_{sim}) \quad (2)$$

Here, R_{meas} and R^i_{sim} are the complete measured and simulated reflectance spectrum, respectively, *T* denotes the transpose, and *C* is the spectral variance-covariance matrix. Both σ_i^2 in Eq. 1 and *C* in Eq.2 are calculated separately for each land cover class based on the measured spectra attributed to that class during classification.

3. RESULTS AND DISCUSSION

Figure 1 shows the accuracy of the RTM inversion results expressed as absolute average deviation, which is the summation of the absolute value of each deviation divided by the number of samples (n=29). Based on the cost function in Eq. 1, differences in retrieval performance between the various sensors are largest for *Cw*. As expected, QuickBird, covering only the visual-near infrared (VNIR), performs very poorly, which can be directly ascribed to the absence of bands in wavelength regions affected by leaf water absorption. The CHRIS Mode 5 configuration, having a few wavebands at the onset of leaf water absorption and a band in the prominent water absorption feature around 970 nm, performs better, followed by the sensors having one or more bands in the highly sensitive shortwave-infrared (SWIR). Concerning *Cdm* and LAI, differences between sensor configurations are not as obvious as for leaf water content. For these variables HyMap 2003 is the best performing configuration followed by the Landsat ETM+ configuration.

Introducing the covariance between spectral bands (Eq. 2) has a varying effect on retrieval accuracy, depending on the band configuration and the considered variable. For *Cw* only the retrieval accuracy for the SPOT HRVIR configuration is significantly altered. Concerning LAI, retrieval accuracy improves for the imaging spectrometers CHRIS and HyMap whereas for the multispectral broadband sensors accuracy decreases. This is what is expected for sensors having only a few wavebands in different characteristic spectral regions, since correlation between these bands is only small and introducing a covariance description based on only a small number of observations (3-13 observations per class) may even increase measurement errors and hence the inaccuracy of the end product. An opposite effect is observed for *Cdm*, i.e. improved retrieval accuracy for the multispectral sensors whereas the results for the hyperspectral sensors deteriorate. Despite this obvious trend, results for *Cdm* should be taken with precaution as spectral reflectance shows only very little sensitivity to changing contents for the cases considered in this study.

If we look at the average accuracy of all variables (Fig. 1, lower right) a generally slight deterioration can be observed when spectral covariance is accounted for, even for both hyperspectral band configurations. The explanation for this has to be sought in the ensemble of variables that is accounted for. This is illustrated by Fig. 2 which shows the estimations of leaf chlorophyll content (*Cab*), LAI, and average leaf angle (ALA), with, and without accounting for covariance between wavebands. The figure reveals that a shift in the estimated variables also takes place for the variables that are not validated in this study. Introducing the covariance description sort of redistributes the weights of the single wavebands in the cost function. While some variables take advantage of this, for others retrieval accuracy is reduced. The latter is exemplified by the loss of accuracy for LAI estimates from multi-spectral band configurations, probably at the benefit of *Cab* estimates which spectrally dominate the visible part of the spectrum.

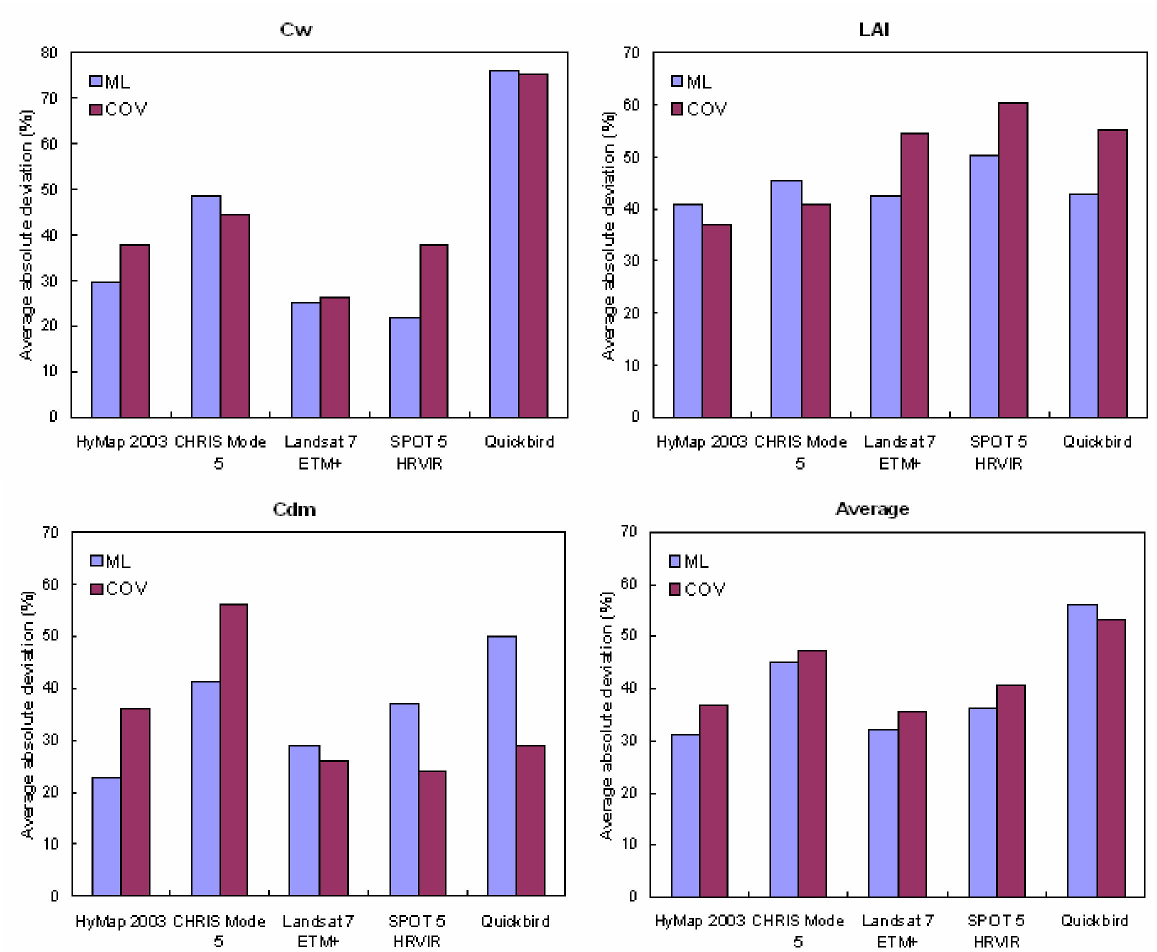

Figure 1. Average absolute deviation (%) as output of radiative transfer model inversion for leaf water content (Cw), leaf dry matter content (Cdm), and leaf area index (LAI). The lower right plot shows the average of the results of the three varaiables. ML indicates the results obtained using the cost function in Eq. 1, COV indicated the result obtained by using the cost function in Eq. 2.

Regarding the average retrieval accuracy of all considered variables, most accurate inversion results were obtained for the full-range, hyperspectral HyMap configuration, shortly followed by the multispectral Landsat ETM+ configuration and at some distance by the SPOT configuration. For the studied variables, CHRIS and Quickbird configurations provided less accurate results. The obtained results indicate that an even distribution of nearly uncorrelated bands across the entire solar-reflective domain contributes more heavily to a robust inversion than a high absolute number of bands in strongly correlating waveband regions, such as provided by CHRIS. The inclusion of SWIR bands seems to lead to a regulation of leaf water retrievals and hence to a stabilization of the complete inversion process.

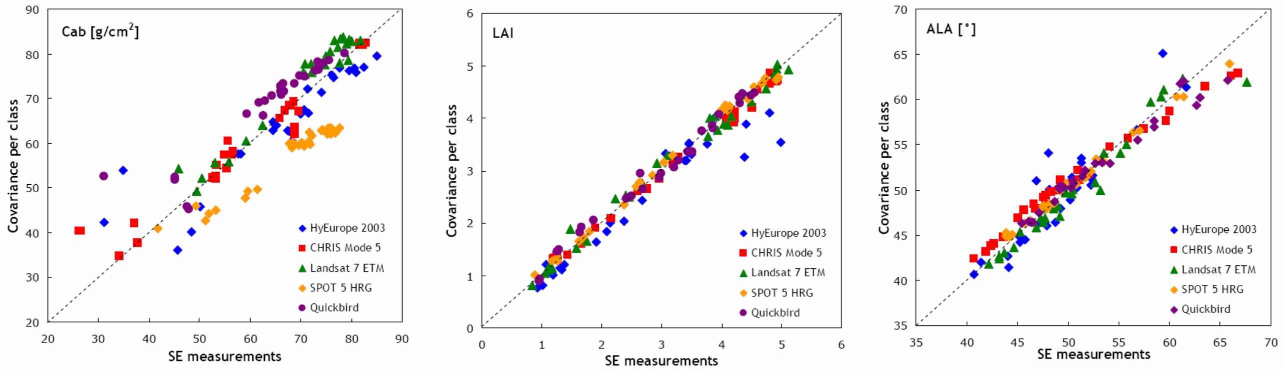

Figure 2. Effect of accounting for spectral covariance on estimates of Cab, LAI and ALA. The effect is shown for 5 different sensor configurations. The x-axis represents the estimations when the cost function of Eq. 1 is used, the y-axis when covariance based on spectra within the land cover classes is introduced (Eq. 2)

4. CONCLUSIONS

In this study we tested the influence of the band configuration (position, band width) on automated radiative transfer model inversion using the CRASh module (Dorigo, 2008). For this purpose, the band configurations of five operational sensors commonly used for vegetation analysis were resampled from field spectra over temperate meadows. The obtained results indicate that an even distribution of nearly uncorrelated bands across the entire solar-reflective domain contributes more heavily to a robust overall inversion than a high absolute number of bands in strongly correlating waveband regions. This notion obtained from measured data may provide an important contribution to sensor development studies, which are often based only on simulated data.

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