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Zagajewski B., Sobczak M., Wrzesień M., (eds)

METHODOLOGY COMPARISON OF QUANTITATIVE LAI RETRIEVAL USING IMAGING SPECTROSCOPY AND GEO-SPATIAL INTERPOLATION IN A SOFT WOOD FOREST

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ABSTRACT

Recent advances in validation of vegetation products have led to new ground based methods to assess the accuracy for small and large spatial footprint sensors. In addition to classical biophysical parameter retrieval (in particular Leaf Area Index (LAI)), current approaches combine photon-vegetation interaction based methods for both, the remote sensing instrument and the ground measurements.

An experiment with the airborne imaging spectrometer HyMap was carried out in the Millingerwaard in the Netherlands in summer 2004 in the framework of an initiative of the Belgian Space Office (Belspo). The Millingerwaard is a large flooding area of the river Rhine, close to the German-Dutch border. The area is a natural reserve and significant supporting data exists (vegetation maps, LIDAR data, CASI data, species composition maps, etc.). The Millingerwaard is a managed natural ecosystem with dominant softwood forests comprised of Populus nigra L. Salix alba L. and Salix purpurea and dense understory namely Urtica dioica L. and Rubus species.

We propose an approach using hemispherical camera pictures combined with a stratified random sampling scheme at plot level and systematic sub-sampling of these plots similar to the VALERI approach. Measurements to assess on-ground the gap fraction, leaf distribution angle, and specie reflectance to estimate LAI have been performed as well. 156 points (e.g., 13 plots, each with 12 sub-sampling points) have been measured and processed using a neural network based approach for validation and calibration purposes of LAI.

LAI is derived on the one hand from the simultaneous HyMap overflight of the test site using a quantitative statistical based approach with calibrated gain factors following the combined approaches of Clevers (WDVI) and Chen (LAI bias correction). On ground spatially distributed LAI maps are generated on plot level (each plot covers 20x20m) and used for calibration and validation of HyMap derived LAI. The second approach includes a spatial interpolation approach that is based on simple kriging with varying local means of the ground measured LAI. The HyMap derived fractional cover is used as an exhaustive secondary variable for the geo-statistical approach.

Both, ground and HyMap derived LAI values are subject to a significant bias, as recently reported in literature. We are using the bias correction to compensate for this difference, and derive true LAI for both methods. The two proposed methods are finally compared to measured ground LAI, where some of the plots remain as validation points that previously have not been used for calibration or interpolation approaches. We conclude that the proposed approaches are very well suited to derive LAI on a forest stand scale with unprecedented accuracy. This is due to the fact that both methods are based on the same principles and we use consistent approaches to measure the interaction of light with vegetation.

1. INTRODUCTION

Nowadays the demand for timely and accurate information on the status and functioning of forest biomes, for a variety of purposes, is increasing. While traditionally forest information was gathered using in-situ methods, the role of remote sensing is becoming more and more central because of the need to the spatial and temporal variability of the key forest processes. So far, high or unknown uncertainty and limited availability of spatially explicit data are the major limiting factors.

Several studies have shown that hyperspectral remote sensing techniques can be applied for quantitative characterization of biophysical and biochemical variables to fulfill this information gap. These studies have shown that biophysical and biochemical variables can be measured with quantifiable uncertainty (Hu et al., 2000; Rast et al., 2004; Koetz et al., 2004; Schaepman et al., 2004 ; Schlerf et al., 2005) .

Leaf area index (LAI) is essential for numerous studies of atmosphere- vegetation interaction, as it is very often a critical parameter in process-based models of vegetation canopy response to global environmental change (Jonckheere et al., 2004). LAI is therefore mentioned as a key variable frequently used as input for crop growth models (Broge and Leblanc, 2001) .

Consequently, recent in-situ and above canopy remote sensing techniques have focused on the measurement and use of LAI as a structural variables since the variables that describe vegetation canopy structure and its energy absorption capacity are required by many of the EOS Interdisciplinary Projects (Myneni et al., 1997).

Therefore, assessment of relevant forest variables can be adequately performed by the use of Radiative Transfer Models (RTM) since these models take into account physical processes describing the interaction of radiation with the diverse canopy components at foliage and canopy levels (Myneni and Ross, 1991). Some models have been compared in performance and quality extensively (Pinty et al., 2001, 2004) and are toady used in many remote sensing derived products (e.g., MODIS MOD15). Recently hemispherical photography has been increasingly used to characterize the structure of canopies and measure the gap fraction directional variation to retrieve variables such as the LAI, fAPAR and clumping factor due to its potential to overcome a number of problems (e.g., greenness confusion and gap size distribution for computing foliage clumpiness) (Jonckheere et al., 2004; Weiss et al., 2004). These approaches are now used to validate LAI on WGCV (global) scales (Privette et al., 2001).

We used regional LAI measurements made with a hemispherical camera and subsequent analysis for calibration and validation purposes of airborne imaging spectrometer data and the retrieved biophysical products from this image will be compared to a geo- statistically interpolated map of LAI over a softwood forest in a river floodplain in the Netherlands.

2. METHODOLOGY AND MATERIALS

2.1. Study Area

The study area for the validation of the remote sensing data (HyMap imaging spectrometer) and ground measurement is located at a large flooding area of the river Rhine, very close to the German-Dutch border called Millingerwaard (c.f.,). It covers approximately an area of 16 km^2. It is situated at 51.5^o N and 5^o E. The mean altitude of this site is 12 m a.s.l. with the minimum of 8.8 m a.s.l. and a maximum of 15.6 m a.s.l. The Millingerwaard is a managed natural ecosystem which covers a wide range of ecology and vegetation of dominant softwood forests comprised of Salix fragilis L. (crack willow), Salix alba L. (white willow), Populus nigra L. (Lombardy poplar); and dense undergrowth namely Urtica dioica L. (common nettle), Calamagrostis epigejos (L.) Roth (wood small-reed), Rubus caesius L. (European dewberry).

2.2. Hemispherical Photograph Acquisition and Processing

The airborne data acquisition was accompanied with ground measurement for calibration and validation purposes. The gap fraction of this softwood forest was assessed with a high-resolution digital camera and by subsequent image analysis. Thirteen sample plots in the closed canopy were selected for ground measurement with digital hemispherical camera.

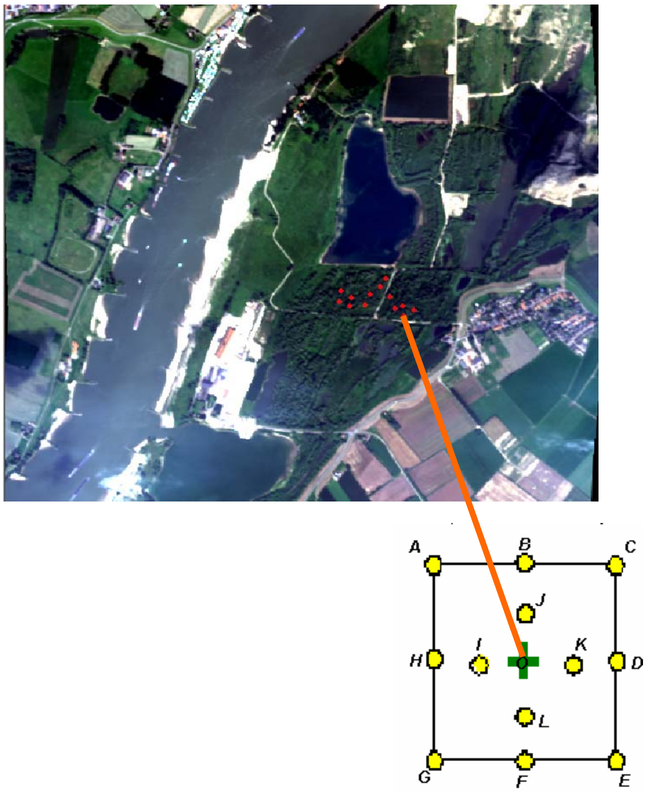

Figure 1: Distribution of sample plots in the softwood forest on top ofHyMap image (top), and field layout for digital hemispherical photography according to VALERI protocol (bottom).

The sample plots were selected following a random sampling scheme to cover the representative soft wood canopy densities. This study site was sampled according to the VALERI protocol (c.f., http://www.avignon.inra.fr/valeri/) as described hereafter. For each elementary sample unit (ESU), a square area of 20 m x 20 m was defined by its 12 subplots, starting from the center point with corner and intermediate measurements. The points within the sample plots are evenly spaced (e.g., 10 m). Each sample plot is established within a minimum of 20 m distance from each other. Measurements of the biophysical parameters describing the spatially distributed canopy structure in general were performed in these plots (c.f., figure 1). These point measurements are also used for krigigng interpolation purposes based on the ground measurements for producing a LAI map for validation of large footprint sensors.

The ground measurements have been carried out after establishing the sample plots in the forests. The hemispherical photographs are captured by the use of a hemispherical digital camera and the images captured were arranged in similar orders in a folder to be processed by the CAN_EYE software developed for this specific purpose (c.f., http://www.avignon.inra.fr/can_eye/).

2.3.Weighted Difference Vegetation Index (WDVI)

Several vegetation indices are incomplete in their physical descriptive basis and as a result of this a simplified reflectance model for estimating LAI, introduced by Clevers (1988, 1989) is chosen for this study. The model computes a corrected near infrared reflectance known as Weighted Difference Vegetation Index (WDVI), by subtracting the contribution of the soil from measured reflectance. It is assumed that the ratio between the reflectance of bare soil in different spectral bands is constant for a given soil background and independent of soil moisture content. This enables to calculate the corrected near-infrared reflectance without knowing soil reflectance.

The WDVI determination requires a coefficient 'C' for correction of the canopy soil composite for soil background changes with varying moisture content. The ratio of the reflectance in two spectral bands can be assumed as a constant and independent of soil moisture content. The existence of a soil line in red and near-infrared wavelength space is widely accepted in literature (c.f., Condit, 1970; Huete, 1985). Based on Clevers (1988), LAI is determined as,

$$LAI = \frac{-1}{\alpha}\ln(1-\frac{WDVI}{WDVI\infty}), \tag{1}$$

$$WDVI = \rho NIR - C\rho RED, \tag{2}$$

and

$$C = \frac{\rho NIRsoil}{\rho RED_{soil}}, \tag{3}$$

Where ρNIR_{soil} is the NIR reflectance of bare soil, ρRED_{soil} is the red reflectance of bare soil, and ρNIR and ρRED is the reflectance of the vegetation canopy. The vales for α and $WDVI\infty$ to retrieve LAI are determined based on the ground measurements. Accordingly, a value of 0.30 and 35 for α and the $WDVI\infty$ is considered respectively.

2.4. Geo-statistical Interpolation

Remote sensing based geo-statistical procedure for softwood forest LAI characterization was done based on ground measurements. Field sampled measurements of LAI and other biophysical variables are interpolated by simple kriging to create a spatially distributed LAI map for the softwood forest structure in the Millingerwaard.

3. RESULTS AND DISCUSSION

3.1. Biophysical products from Hemispherical Photography

3.1.1. LAI

Hemispherical photograph processing by the use of neural network based software, CAN_EYE resulted in an estimation of both, effective and true LAI. The result of the analysis from the softwood forest gives LAI values ranging from 4.7 - 6.5 m^2/m^2 and 2.9 - 4.0 m^2/m^2 for true and effective LAI respectively (c.f., table 1). These results are mainly explaining the values in the forest areas and as a result, both the effective and true LAI are exhibiting a narrow interval.

Table 1. Summary of all ground measured biophysical products in the 13 VALERI sample plots in softwood forests of the Millingerwaard derived using CAN_EYE.

Plot no.	CE_LAI_{eff} [m^2/m^2]	CE_LAI_{true}[m^2/m^2]	CE_fCover	CE_gap fraction	CE_fAPAR
1	3.9	5.9	0.96	0.24	0.55
2	3.4	5.5	0.94	0.20	0.48
3	4	5.8	0.95	0.18	0.39
4	3.4	5.7	0.93	0.25	0.49
5	3.9	6.2	0.97	0.17	0.41
6	3.5	6	0.94	0.22	0.51
7	3.8	6.5	0.94	0.18	0.41
8	3	5.1	0.89	0.27	0.51
9	3.4	5.1	0.91	0.23	0.46
10	2.9	4.7	0.84	0.32	0.66
11	3.3	5.6	0.93	0.26	0.56
12	3.5	5.1	0.93	0.20	0.37
13	3.7	5.5	0.92	0.21	0.45

The estimation of all the biophysical products from the ground measurements using hemispherical camera in general and the LAI in particular could be liable to different sources of errors which can occur at any stage of image acquisition as in any remote sensing instrument or during image analysis. Rich et al., (1993) mentioned the possibility of errors as with any remote sensing technique, at any stage of image acquisition or analysis. Nevertheless, our results computed from the ground measurements gave good estimation of biophysical variables.

3.1.2.FRACTIONAL VEGETATION COVER (FCOVER)

The mean fCover values observed from all the sampled plots is 93% with a minimum and maximum fCover of 84% and 97% respectively (c.f., table 1). This is a very closed canopy with little openings. In this heterogeneous softwood forest structure, especially the presence of dense undestory contributed to the larger value of fCover. According to the results from the hemispherical camera measurements processed with CAN_EYE, the correlation between the effective LAI and the fCover has showed an r^2 of 0.69. This also confirms the independent relationship of the two products namely LAI and fCover.

3.1.3. Fraction of Absorbed Photosynyhetically Active Radiation (fAPAR)

The average value of ground measured instantaneous fAPAR for the whole sampled plots of the softwood is 0.48. The same principle of computation from the upward hemispherical measurement is considered and it is derived using the CAN_EYE software.

3.2. Biophysical Products Derived from HyMap

3.2.1. LAI

The summary of all the biophysical products derived from the HyMap image for all VALERI sample plots are shown in Table 2. LAI is retrieved from the hyperspectrral remote sensing data by Weighted Difference Vegetation Index WDVI (Clevers, 1989) which is corrected for soil factor was used to retrieve the LAI from the airborne measurements (HyMap image) after calibrating with ground measured LAI values.

Table 2. Summary of biophysical products derived from HyMap image per sample plot for the softwood forest at the Millingerwaard; fCover is derived using Green Red Vegetation Index (GRVI) and Linear Spectral Unmixing (SUM).

Plot no.	WDVI	HyMap LAI_{eff}	HyMap LAI_{true}	fAPAR	GRVI_fCover	SUM fCover
1	19.01	3.13	4.02	0.77	0.60	1.00
2	22.91	3.54	5.77	0.84	0.60	0.94
3	18.85	2.58	3.96	0.76	0.65	0.99
4	22.39	3.40	5.48	0.83	0.61	0.88
5	23.57	3.73	6.16	0.85	0.59	0.98
6	18.40	2.49	3.80	0.75	0.61	0.97
7	20.88	3.03	4.76	0.81	0.58	1.00
8	20.56	2.95	4.62	0.80	0.64	0.96
9	22.71	3.49	5.66	0.84	0.63	0.97
10	21.47	3.17	5.03	0.82	0.63	0.88
11	21.14	3.09	4.88	0.81	0.66	0.95
12	21.68	3.22	5.13	0.82	0.63	1.00
13	19.38	2.69	4.16	0.77	0.56	0.88

The true and the effective LAI are determined by optimizing the α and the WDVI$^{\infty}$ is based on the ground measured values. Accordingly the calibration of LAI value was done by taking the measured LAI from the hemispherical photography as a reference LAI value for a particular point of interest. The constant for an α and WDVI$^{\infty}$ from the literature was suggested to be 0.5 and 60 (Strub, 2001; Kneubuehler, 2002). But these values get different weight based on the land cover type. In the case of forest area the reflectance is scattered in the large volume of the forest canopy and also affected by shadows in the forest floor. As a consequence the proposed values for agricultural crops could not be applicable for forest areas. The spatially distributed LAI map using WDVI is finally produced for the Millingerwaaard soft wood area (c.f., figure 2a).

For testing the sensitivity of different algorithms towards estimating LAI, the algorithms of Reduced Simple Ratio (RSR) based on Chen et al. (2002), Fractional Vegetation Cover (FVC) based on Roujean and Lacaze (2003) and NDVI based on Weiss et al. (2002) methods were also used. These vegetation indices are considered and implemented as suggested by the authors and their sensitivity is tested against the ground measurements spatially distributed LAI map (see fig 2 b, c and d), show different LAI values when compared to each other.

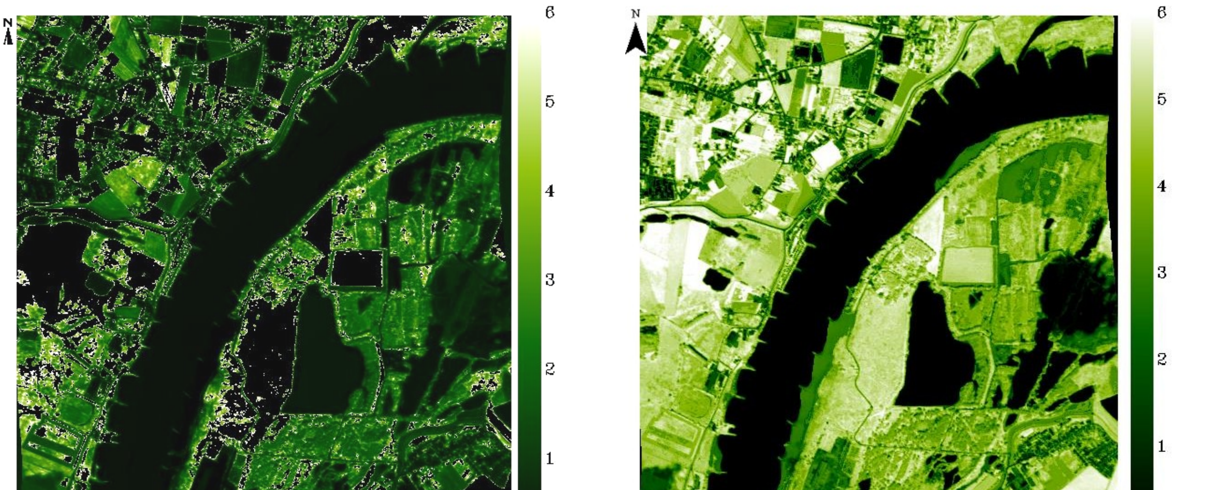

Figure 2: Spatially distributed LAI map of the Millingerwaard based on four different retrieval schemes: a). WDVI, b) RSR, c) FVC, and d) NDVI (see text for references and abbreviations).

The overall results from the different algorithms are compared to the ground measured LAI value (c.f., figure 3). The comparison was done by aggregating the 5m spatial resolution of HyMap pixel to 20 meters. By doing so, the result clearly shows the LAI estimated from calibrated HyMap image using the WDVI and the one derived based on the RSR method based on Chen et al. (2002) are showing closer values of LAI. A very low value of LAI is observed after applying FVC method based on Roujean and Lacze (2003).

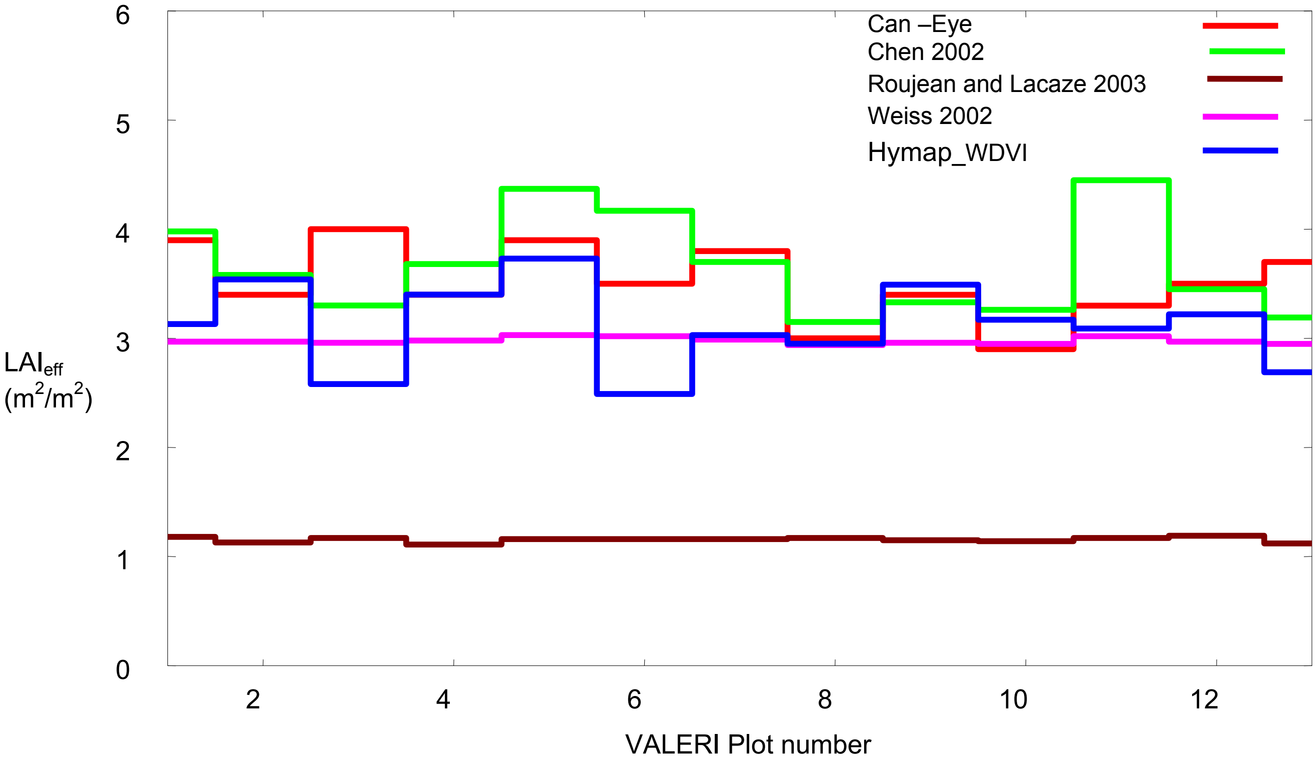

Figure 3: Graphical plot of the results of application of different algorithms to HyMap image and CAN_EYE derived LAI values at a plot level in the softwood forests in the Millingerwaard.

Therefore, the different methods followed showed different trends and value when compared to the ground sample LAI values. In the case of Roujean and Lacaze (2003), the derived LAI values are very low and couldn't estimate the LAI as it was demonstrated by the others (i.e., by using CAN_EYE, RSR and WDVI). This could be due to application of the broad band algorithm (Polder) to a narrow band imaging spectrometer data. LAI derived from HyMap image by using WDVI and Chen et al. (2002) is best when compared to CAN- EYE at plot level. The correlation of LAI based on WDVI and RSR following Chen et al. (2002) showed high value (r^2 = 0.88). The empirical method for optimization of $WDVI_{\infty}$ and α in the case of WDVI and the use of SWIR band in the case RSR have contributed to the better estimation of LAI.

3.2.3. Fraction of Vegetation Cover (fCover)

The fractional vegetation cover was retrieved by calculating Green Red Vegetation Index (GRVI) and abundance of soil and vegetation using linear spectral unmixing (c.f., table 2). The fCover retrieval by GRVI and spectral unmixing are analyzed to compare the performance of these methods in assessing the fraction of the vegetation with the ground measured values.

3.2.3. Fractional Vegetation Cover Using Linear Spectral Unmixing Approach

The calculated mean fCover ranged between 0 and 1 with a mean of 0.91(c.f., table1) and with a standard deviation of 0.212 over the total softwood area of the Millingerwaard image.As it has been reported from the quality assessment of the image, most of the pixels especially in the forest area are covered with vegetation and the resulting fCover in this area is also high. Since the forest floor is covered with dense understory and canopies of the trees, the majority of the pixels showed an fCover value of one.

3.2.4. Fraction of Absorbed Phothosynthetically Active Radiation (fAPAR)

The coefficients for computing fraction of absorbed photosynthetically active radiation are also determined based on the field measurements. The LAI derived from HyMap by WDVI method is taken to estimate the fAPAR. Consequently, the way the LAI is estimated affects the estimation of fAPAR in the same manner. The fAPAR, which is related to LAI, and its constants are determined from the field measurements and the coefficient values are set to the following and resulted in average value of 0.81.

$$fAPAR = b_o(1 - b_1 Exp(-LAIb_2)), \tag{4}$$

Where, b_0 = 0.9, $b1$ = 1.0, and b_2 = 0.38. The initial values for the range of the coefficients are taken from literature (Keneubuehler, 2002; Strub et al., 2001).

3.2.5. Geostatistically Interpolated LAI

The spatial interpolation of LAI index for the whole area of the softwood was done by the support of fractional cover and produced the spatially distributed LAI map based on the ground measured data .The fractional cover used for this case is derived from the HyMap image through spectral unmixing technique. Fractional cover in an unvisited area was used to interpolate the LAI from the areas so that the interpolation is done in the same relationship with the initial correlation of LAI and fCover.

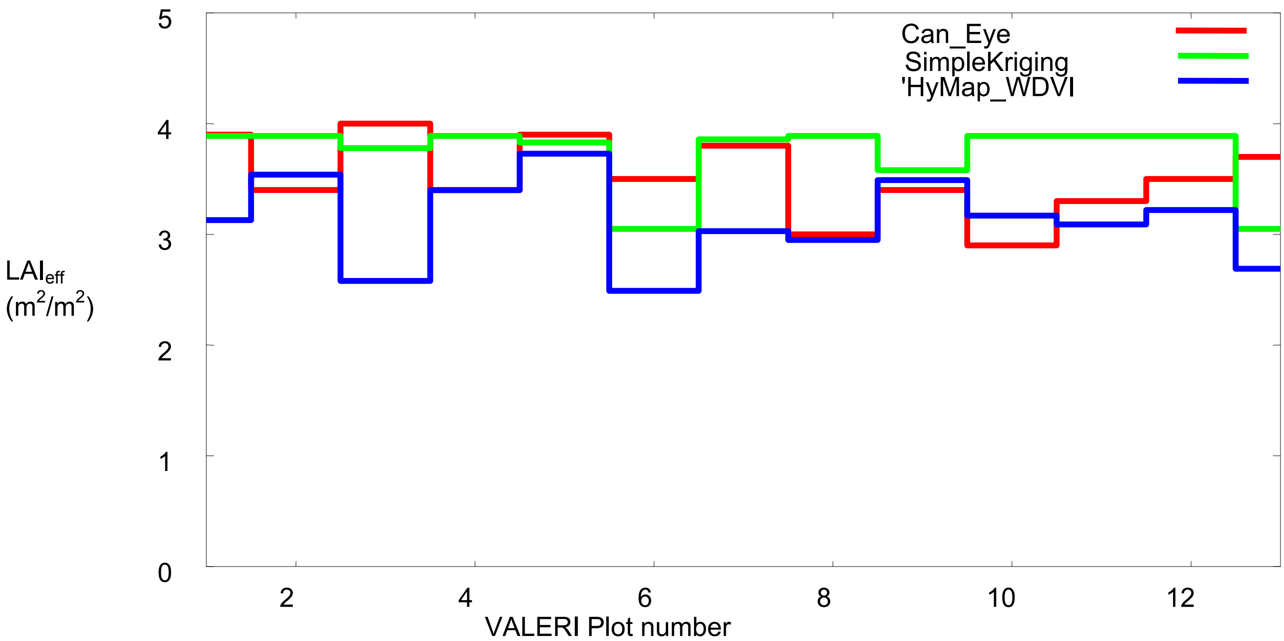

Figure 4. LAI values per VALERI sample plot vs. LAI values derived using kriging and the NN based software CAN_EYE in the softwood forest at the Millingerwaard.

Based on the correlation of the two products (fractional cover from spectral unmixing and LAI), spatial interpolation of the LAI was applied by using a secondary variable. Accordingly, the fractional cover and the LAI are correlated and the spatially distributed LAI map is produced by simple kriging method.

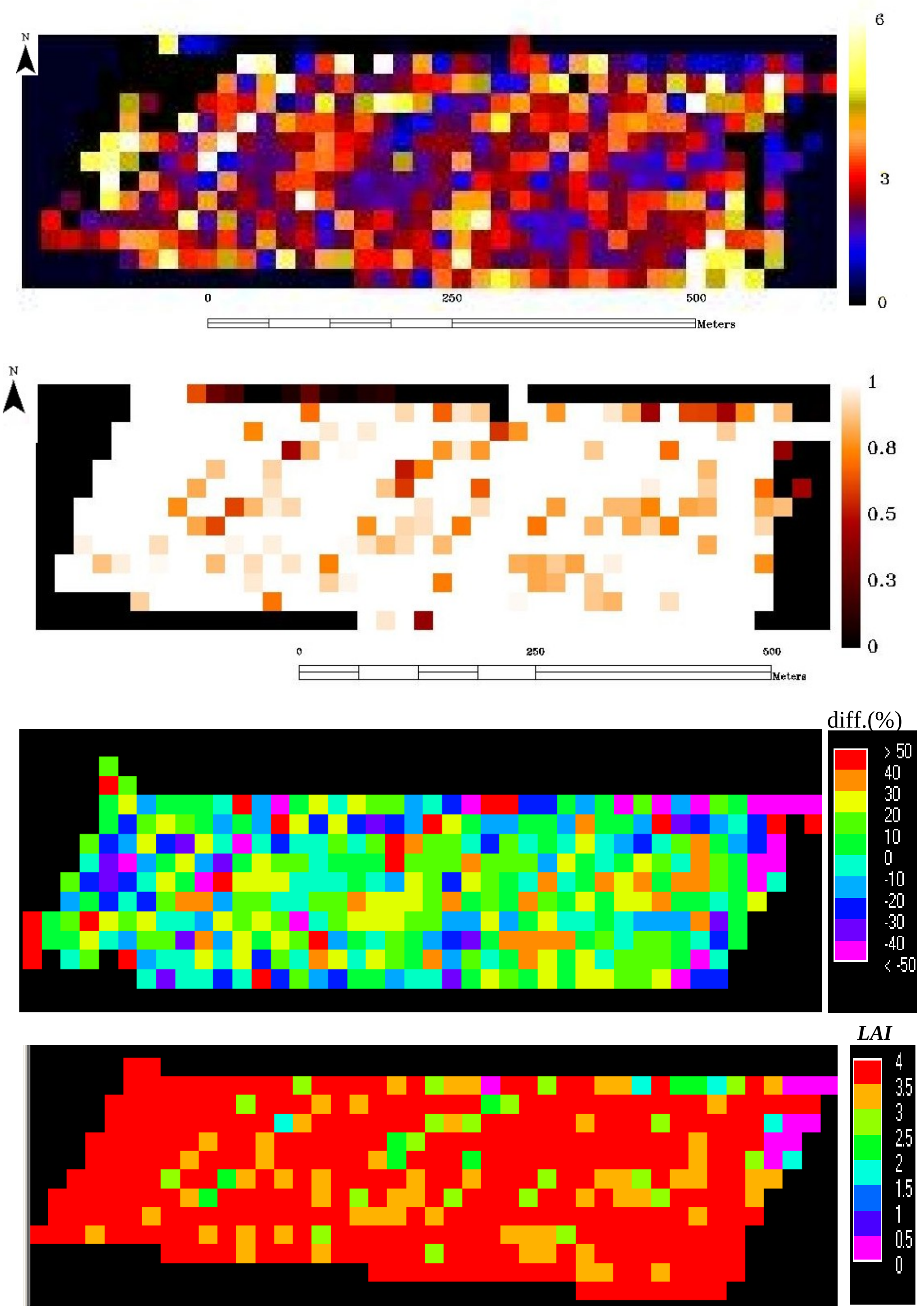

Figure 5: Top: LAI derived from HyMap based on WDVI in the softwood forest at the Millingerwaard, Middle-top: Spatially distributed map of LAI interpolated using simple kriging, Middle-bottom: fCover map (pixel size aggregated to 20x20 meter), and Bottom: Percentage difference map of LAI between WDVI and the geo-spatial interpolation approach.

Generally, the mean of spatially interpolated LAI map by the use of simple kriging(c.f., figure 5 middle-top showed almost similar LAI values with LAI map derived from HyMap by WDVI (c.f., figure 5 top). Forest areas with lower fCover values exihibit lower LAI values. A slight difference between the mean of the estimated and measured values (c.f., figure 5 bottom) might be caused by taking a point measurement values to produce a spatially distributed map within the sampled plots (i.e the interpolation of point measurements to an aggregated block of HyMap pixels with 20 x 20 meter).

4. CONCLUSIONS

The ground measurement of the forest structure by hemispherical photography approach is found to be an easy and quick to use and accounts for clumping factor, which is the major problem in underestimation of LAI and all the biophysical products derived form remotely sensed images. Biophysical products in the softwood forests at Millingerwaard are therefore assessed and estimated for calibration of the HyMap data using this method and subsequent analysis by a neural network based system software.

The geo-statistical interpolation of LAI using simple kriging with varying local mean based on the HyMap derived fractional cover has resulted in spatially distributed map of LAI which can be used for validation of larger footprint sensors (eg., MERIS and MODIS) with good accuracy (scaling issues).

Generally, the selected approaches enabled to produce validated continuous fields of biophysical products over the study area. This derived data can be further used as an input in land biosphere system or in (global) validation of LAI products (e.g. BELMANIP, CEOS-LPV).

ACKNOWLEDGEMENTS

This work was carried out in the framework of the HyEco'04 campaign. We thank the Belgian Space Office (BELSPO) for support through their STEREO programme. The field work was carried out with the support of VITO, Alterra, Vrije Universiteit Brussel, and the Université Libre de Bruxelles.

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