Crop specific monitoring of biophysical variables at regional scale using MODIS imagery

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Abstract – The trade-off between observation frequency, geographical coverage and spatial resolution has often hampered the use of remote sensing for estimating crop specific biophysical variables at wide scales. In the framework of the GLOBAM project, a methodology is proposed to tackle the problem by working with medium resolution imagery (MODIS, 250m) and taking special care to ensure the adequacy between the observation support (the pixel) and the target (the crop specific field). The approach is tested over the winter wheat season of 2007 in two large contrasted agro-ecological regions: northern Europe and the north China plains. The results show that a significant improvement over standard MODIS products can be achieved by focusing on the pixels whose ground projection corresponds almost exclusively to the target crop.

Keywords: Biophysical variable retrieval, crop specific monitoring, regional scale, pixel purity, MODIS.

1. INTRODUCTION

Accentuated inter-annual variability of climatic conditions will increase the interest in monitoring specific crops at national, regional and global scales. However, the trade-off between observation frequency, geographical coverage and spatial resolution has often hampered the use of remote sensing for estimating crop specific biophysical variables at wide scales. Most biophysical variable products are derived from remote sensing at regional or global scale which provides continuous maps at a resolution of 1-3 km (Baret et al. 2007; Myneni et al. 2002). Although this full exhaustive coverage is interesting for some applications, such products are optimized for all land cover types and for surfaces of different sizes, which is not always adequate for an application where a single crop is observed.

For crop growth monitoring high observation frequency is mandatory, especially when anomalies due to climatic variability are to be detected. This often comes to the expense of a coarser spatial resolution which in turn results in measuring a signal originating from a larger and potentially more heterogeneous area. This bottleneck can be surmounted using imagery from medium spatial resolution sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard of TERRA and AQUA. However, in this context the adequacy between the observation support (the pixel) and the target (the crop specific field) must be assured. Indeed, the process of gridding, i.e. assigning an observation to a predefined system of grid, introduces a “pixel-shift” which can be quantitatively described by the notion of “observation coverage” or *obscov* (Wolfe et al. 1998). *Obscov* is a ratio between: (1) the intersection area between the nominal observation and the grid cell; and (2) the nominal area of the observation. Tan et al. (2006) used this *obscov* value, which is provided along with MODIS reflectance products, to show the impact that gridding artifacts may have on compositing and band-to-band registration of MODIS data. These problems are compounded by the large across-track scan angle range of MODIS which results in view zenith angles (VZA) that can reach 65° increasing dramatically the size of the observation support.

The objective of this study is to explore the potential of MODIS 250m imagery for monitoring biophysical variables of a specific crop at a regional scale. This research is realized in the framework of GLOBAM project which aims at developing crop specific monitoring capabilities by Earth observation over different test sites distributed over 3 continents. The problem of pixel/support adequacy is managed in both space and time by taking into account the sensor's spatial response and the *obscov* and VZA values provided by the products. The methodology is based on the assumption that in order to characterize the crop dynamics, it is better to focus on satellite observations which are acquired over almost pure pixels rather than mixed pixels. This implies that biophysical variable time series are produced only for the subset of pixels for which the spectral information comes exclusively (or almost exclusively) from the targeted crop. Over an area with homogeneous agro-climatic growing conditions and similar crop practices, the general growth of a specific crop can be characterized by a subset of such time series corresponding to the larger fields of the landscape. Even in regions where the mean field size is significantly smaller than the spatial resolution, a set of larger fields can effectively represent the regional growth dynamics of a given crop without adding a significant bias (Guissard et al. 2004).

2. MAIN BODY

2.1 Methodology

The method presented here is tested on winter wheat (*Triticum aestivum*) for a single season in 2007. Two GLOBAM sites of 300 by 300 km are selected in different agro-ecological regions: northern Europe (NEU) and the north China plains (NCP). The size of the wheat fields on the European site are of the same order of

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magnitude as the ground projection of the instantaneous field of view of MODIS. The landscape is also very fragmented, i.e. adjacent fields are often covered by different crops. Conversely, the Chinese site has much smaller fields but the same crop is cultivated on adjacent fields.

To identify the medium resolution pixels for which the information comes almost exclusively from the target crop, a crop specific mask at a fine spatial resolution is necessary. In order to cover the large extent required to work at regional scale, wide-swath AWiFS imagery acquired early in the crop growing season was classified by maximum likelihood in order to generate a crop specific map. When possible, multi-temporal classification is realized.

Due to the point spread function (PSF), the observation encoded in a pixel originates from a surface which is larger than its rectangular ground projection (Huang et al, 2002). Therefore this whole surface must be considered when determining whether a MODIS pixel can be considered as “pure”. To do so, a model of the sensor PSF is constructed using information provided by the MODIS Characterization Support Team (MCST). This model is convolved over the fine resolution crop mask. The resulting image maps the purity (with respect to the target crop) of the theoretical observation of the medium resolution sensor. This information is then upscaled to the MODIS grid in order to assign to every cell an estimation of the percent of the surface of the target crop which contributes to the reflectance value encoded in the pixel. In this study, a threshold of 90% of land cover purity is used to define the pixels that must be monitored.

Time series of NIR and RED reflectances are then compiled for each of the 250 m accepted pixels. The collection 5 daily products from both MODIS AQUA and TERRA are used jointly. Values of *obscov* and VZA are retained for each measurement. The best reflectance measurements are expected to have high *obscov* values and low VZA. Both VZA and *obscov* are independent of time. Figure 1 illustrates the influence of these observation parameters on the NIR band for all the measurements: an increasing *obscov* tends to reduce the reflectance whereas the inverse is observed with VZA. Furthermore, the variance of the reflectance is also reduced when *obscov* is high and VZA low.

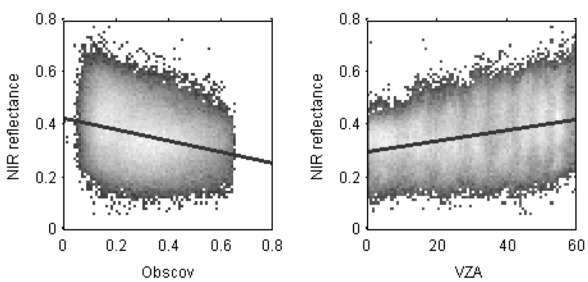

Figure 1. Influence of (a) *obscov* and (b) VZA on the NIR reflectance. The density plots are based on the entire 90% pure time series of the NEU site during the first 200 days of 2007.

Biophysical variables are derived from the time-series using the algorithm developed for the CYCLOPES products (Baret et al., 2007). This algorithm is based on the inversion of a radiative transfer model (SAIL model developed by Verhoef (1984)) using a neural network approach. The use of a radiative transfer model helps the methodology to be applicable in different agro-ecological contexts. Indeed, the biophysical variable retrieval is based on physics rather than locally adjusted empirical relationships. Using a neural network to achieve the inversion procedure helps rendering the approach computationally efficient. Both these characteristics are interesting in an operational monitoring perspective. The output biophysical variables are leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR) and vegetation cover fraction (FCOVER).

The biophysical variables are derived for every single observation at every 90% pure pixel. On one hand, a better estimation of these variables can be expected for the input observations with higher *obscov* and lower VZA. On the other hand, limiting the biophysical variable time series only to estimations of high quality may jeopardize the temporal coverage. In order to take full advantage of all the data, the time series of biophysical variables are smoothed using a polynomial regression filter which favours high *obscov* and low VZA but still uses all available observations. The weighting functions are shown on Figure 2. In this paper, a first order polynomial is used and the variance of the Gaussian kernel along the temporal axis is 50.

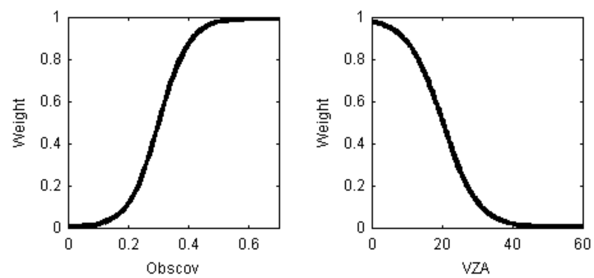

Figure 2. Weighting functions of the polynomial regression filter for (a) *obscov* and (b) VZA.

2.2 Results

An example of the resulting smoothed time series for each biophysical variable on a single 90% pure pixel is shown, for both NEU and NCP sites, on Figure 3. The temporal profile of the NEU site, which is representative of the whole dataset, reveals the severe lack of data during long time periods due to overcast weather. Data availability is not an issue for site NCP but early values might be affected by snow undetected by the MODIS quality flags.

Ground LAI measurements are used to validate the biophysical variable estimates over the NEU and NCP sites (see Figure 4). On the NEU site, the LAI was measured using a LiCor LAI-2000. Measurements were performed on large fields which correspond to 90% pure MODIS pixels around anthesis (onset of flowering) when the LAI values are expected to be highest. For the NCP site, the ground LAI values are available along the whole season. These are obtained by measuring the length and width of a representative sample of leaves. This measuring method, unlike that of the LAI-2000, accounts for stacked leaves resulting in higher values. On the other hand, the LAI-2000 measures do not distinguish between leaves, stems or other organs and should therefore be considered as a plant area index (PAI).

The estimated LAI is also compared to the standard LAI MODIS product (see Figure 5) which is calculated by inverting the radiative transfer problem using a look-up table (Myneni et al. 2002). However, the spatial resolution of this product is 1km.

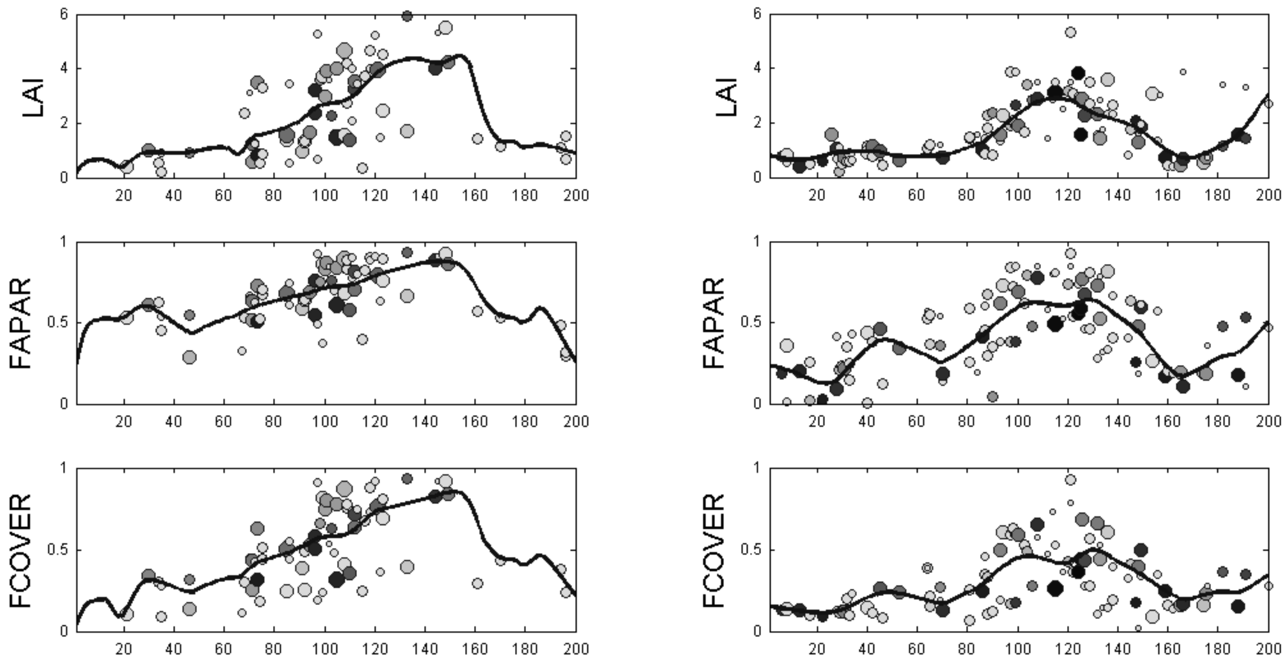

Figure 3. Smoothed time series for the biophysical variables of interest for the NEU site (on the left) and for the NCP site (in the right). The larger dots indicate favourable *obscov* values while the darker dots indicate favourable VZA.

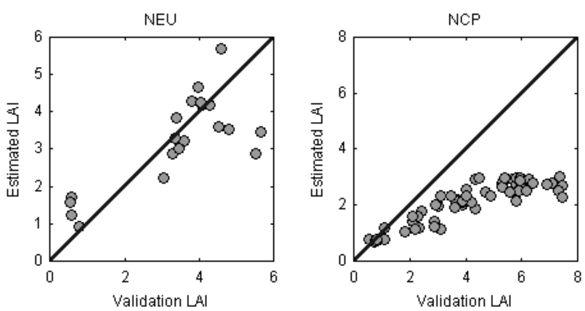

Figure 4. The relationship between estimated LAI and field measurements for (a) NEU site and (b) NCP site.

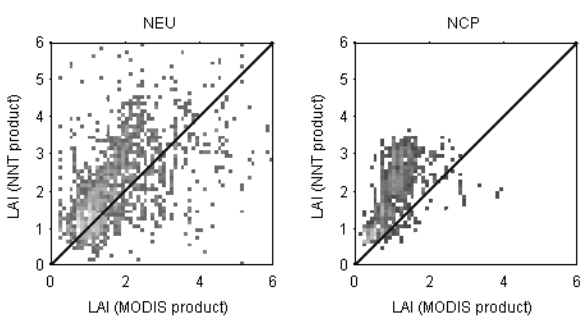

Figure 5. Comparison of the LAI estimates by the method presented in this paper with the MODIS Collection 5 product for both sites

Therefore, this comparison is done for indicative purposes only as the MODIS LAI pixels do not necessarily cover a single crop whereas the 250m pixels used in the approach presented here have been selected to ensure 90% purity.

The validation of the proposed methodology against ground truth is resumed in Table A using the Root Mean Square Error (RMSE) and the coefficient of determination (R^2). For comparison purposes, the validation was also performed: (i) on punctual (i.e. non-smoothed) LAI estimates; (ii) on LAI smoothed using a polynomial regression filter with the same characteristics as the one used earlier except that it is not weighted by *obscov* and VZA; and (iii) on the MODIS collection 5 products.

Table A. Validation results with respect to the ground measured LAI. N is the number of validation samples.

Site	**N**	**Product**	**R^2**	**RMSE (detrended)**
NEU	18	Raw estimates	0.059	2.998
	27	Simple smoothing	0.433	1.347
	20	Weighted smoothing	0.581	1.015
	17	MODIS Collection 5	0.125	2.107
NCP	59	Raw estimates	0.468	2.497 (0.768)
	61	Simple smoothing	0.796	2.452 (0.273)
	61	Weighted smoothing	0.787	2.558 (0.273)
	45	MODIS Collection 5	0.269	3.818 (0.428)

Since the reference for the NCP site is planimetric LAI, a significant bias is observed in all products (especially for the higher LAI values) which affects the RMSE. The RMSE is therefore recalculated for this site after removing the trend which is modelled by a second order polynomial.

Note that the number of validation samples is variable between the product types. The raw LAI estimates were selected when they were located within ±3 days of the field measurement. For the NEU site where cloud coverage was an issue, this reduced significantly the number of usable samples. The number of validation samples is not constant for the filtering techniques because unrealistic estimations (above LAI=6) where removed from the dataset. Such high estimations may occur if the smoothing was too close to badly estimated LAI values. For the MODIS LAI Collection 5 products, which are provided every 8 days, linear interpolation is used to find the value corresponding to the field measurement. However this is not done when values in the time series are missing, resulting in a reduced number of validation samples.

2.3 Discussion

The number of ground measurements is limited and might not be enough to fully characterize the performances of the different products. Nevertheless, inter-comparing the different products listed in table A do help to evaluate the method presented in this paper.

As expected, the non-smoothed LAI estimates perform poorly due to the variable quality of the input reflectances. Figures 2 and 3 illustrate how variable the estimations can be. Smoothing the LAI estimates significantly improves the performance.

The comparison of the results of the two smoothing methods reveals that taking into account the quality by means of the weights improves the performance only for the NEU site. The best explanation relies on the structure of the agricultural landscapes. Since the NEU is much more fragmented, pixel purity is threatened when the observations are done with higher VZA and when the *obscov* is low. In the Chinese landscape, if the observation support is larger than expected (due to high VZA and low *obscov*), the impact on the reflectance is reduced because areas surrounding the support are very likely covered by the same canopy.

For both sites, the RMSE and the R^2 indicate that the LAI estimated by the present approach is closer to ground truth than the MODIS standard product. The comparison of the retrieval methods has shown that NNT does perform better than the MODIS look-up table (Weiss et al. 2007). However, in this case the NNT method is favoured by the input data of purer observations which is filtered both in the spatial and temporal domains. Furthermore, the scale of the products is different (250 m vs. 1 km).

3. CONCLUSIONS

Time series of biophysical variables for a specific crop were successfully retrieved from MODIS data. By focusing the attention to purer crop specific pixels, the resulting product performs better than the standard LAI MODIS product. Further research is necessary to comfort these conclusions since they could be affected by the choices in the pixel purity tolerance (in this case 90%), in the description of quality (weighting functions for *obscov* and VZA) and in the characteristics of the filter (size, order). Nevertheless, the results presented in this paper do show that to monitor winter wheat over the studied landscapes, it is worthwhile to rely on a method taking into account the adequacy between the observation support (the pixel) and the target crop specific field.

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