



**HAL**  
open science

## **Crop specific green area index retrieval from MODIS data at regional scale by controlling pixel-target adequacy**

Grégory Duveiller, Frédéric Baret, Pierre Defourny

### ► **To cite this version:**

Grégory Duveiller, Frédéric Baret, Pierre Defourny. Crop specific green area index retrieval from MODIS data at regional scale by controlling pixel-target adequacy. *Remote Sensing of Environment*, 2011, 115 (10), pp.2686-2701. <10.1016/j.rse.2011.05.026>. <hal-01317521>

**HAL Id: hal-01317521**

**<https://hal.science/hal-01317521v1>**

Submitted on 29 May 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY-NC-ND 4.0 - Attribution - Non-commercial use - No Derivative Works - International License

1 Crop specific green area index retrieval from MODIS  
2 data at regional scale by controlling pixel–target  
3 adequacy

4 Grégory Duveiller<sup>a,\*</sup>, Frédéric Baret<sup>b</sup>, Pierre Defourny<sup>a</sup>

5 <sup>a</sup>*Earth and Life Institute, Université Catholique de Louvain, 2/16 Croix du Sud, B-1348*  
6 *Louvain-la-Neuve, Belgium*

7 <sup>b</sup>*Environnement Méditerranéen et Modélisation des Agro-Hydrosystèmes (EMMAH),*  
8 *INRA-UMR 1114, Domaine Saint-Paul, Site Agroparc, 84914 Avignon, France*

---

9 **Abstract**

Information on vegetation status can be retrieved from satellite observations by modelling and inverting canopy radiative transfer. Agricultural monitoring and yield forecasting could greatly benefit from such techniques by coupling crop growth models with crop specific information through data assimilation. An indicator which would be particularly interesting to obtain from remote sensing is the total surface of photosynthetically active plant tissue, or Green Area Index (GAI). Currently, the major limitation is that the imagery that can be used operationally and economically over large areas with high temporal frequency have a coarse spatial resolution. This paper demonstrates how it is possible to characterize the regional crop specific GAI range along with its temporal dynamic using MODIS imagery by controlling the degree at which the observation footprints of the coarse pixels fall within the crop-specific mask delineating the target. This control is done by modelling the instrument's point spread function and by filtering out less reliable GAI estimations in both the spatial and temporal dimensions using thresholds on 3 variables: pixel purity, observation coverage and view zenith angle. The difference in performance between MODIS and fine spatial resolution to estimate the median GAI of a given crop over a 40×40 km study region can be reduced to a RMSE of 0.053 m<sup>2</sup>/m<sup>2</sup>. The consistency between fine and coarse spatial resolution GAI estimations suggest a possible instrument synergy whereby the high temporal

---

\*Corresponding author currently at Institute for Environment and Sustainability, European Commission - Joint Research Centre, Via Fermi 2749, Ispra, Varese, Italy. Tel: +39 033278 9161. Fax: +39 033278 3033

*Email addresses:* [gregory.duveiller@jrc.ec.europa.eu](mailto:gregory.duveiller@jrc.ec.europa.eu) (Grégory Duveiller),  
[frederic.baret@avignon.inra.fr](mailto:frederic.baret@avignon.inra.fr) (Frédéric Baret), [pierre.defourny@uclouvain.be](mailto:pierre.defourny@uclouvain.be) (Pierre Defourny)

resolution of MODIS provides the general GAI trajectory and while high spatial resolution can be used to estimate the local GAI spatial heterogeneity.

1 *Keywords:* Green area index, leaf area index, canopy radiative transfer, crop  
2 growth monitoring, regional scale, MODIS, pixel purity, observation coverage,  
3 Point Spread Function

---

## 4 **1. Introduction**

5 Monitoring vegetation dynamics over the Earth's surface is of paramount  
6 importance for agricultural, hydrological, meteorological and climate applica-  
7 tions. The surface of green foliage is the main interface between atmosphere  
8 and vegetation, thereby governing the exchanges of energy, water and carbon.  
9 Both the radiative transfer and the functioning of a vegetation canopy are driven  
10 by the leaf area index (LAI), defined as half the total developed area of green  
11 leaves per unit of ground horizontal surface area (Chen & Black, 1992). LAI  
12 is a state variable in various land surface models, and more specifically in crop  
13 growth models (e.g. CERES (Ritchie & Otter, 1985), WOFOST (van Diepen  
14 et al., 1989) and STICS (Brisson et al., 1998)). Providing an estimation of such  
15 biophysical variables at relevant spatial and temporal resolutions can assist and  
16 potentially improve modelling approaches by either forcing the model or by  
17 controlling its temporal trajectory using assimilation techniques (Moulin et al.,  
18 1998; Cayrol et al., 2000; Dorigo et al., 2007).

19 Earth observation from satellite remote sensing provides synoptic and timely  
20 coverage which can be used to derive land surface variables such as LAI over  
21 large geographic extents. It is however necessary to characterize and invert the  
22 complex and non-linear relationship between canopy structure and reflectance  
23 (Myneni et al., 1995). For crops such as cereals in which all main aerial plant  
24 organs (leaves, stems, ears) are green and photosynthetically active, it is more  
25 appropriate to use the term of green area index (GAI) to refer to the biophys-  
26 ical variable retrieved from remote sensing since the radiance measured by the  
27 instrument is made of electromagnetic radiation reflected from all plant organs

1 (Duveiller et al., 2011). While estimating such information on canopy status  
2 at field level from high spatial resolution imagery has been done throughout  
3 the past decades with increasing performances, a real challenge is to estimate  
4 it over large geographical extents. LAI datasets have been produced at global  
5 scale (*e.g.* Sellers et al., 1994; Los et al., 2000; Myneni et al., 2002; Masson et al.,  
6 2003; Deng et al., 2006; Baret et al., 2007) but their spatial resolution (at best  
7 1 km) is much too coarse to be crop specific over many landscapes across the  
8 world.

9 Satellite remote sensing is intrinsically confronted to a trade-off between  
10 spatial, temporal, spectral and radiometric resolutions. The high observation  
11 frequency necessary to detect anomalies due to climatic variability comes at  
12 the expense of coarser observation supports, which in turn results in measur-  
13 ing a signal originating from a larger and potentially more heterogeneous area.  
14 Although technological improvements are bound to provide finer spatial reso-  
15 lution data with more frequent observations, coarse instruments will retain a  
16 valuable interest since they provide a long time record. Medium or moderate  
17 spatial resolution instruments, best represented by MODIS on-board of Terra  
18 and Aqua platforms (Salomonson et al., 1989), MERIS on-board of ENVISAT  
19 (Rast et al., 1999) and the forthcoming OLCI which will be on-board of the  
20 GMES Sentinel-3 platform (Nieke et al., 2008), offer an interesting combination  
21 of spatial and spectral resolutions with high temporal repetitivity. However,  
22 given their spatial resolutions (pixel size ranging from around 250 to 500 m),  
23 it is still required to address the issue of spatial heterogeneity in order to have  
24 crop specific information over many agricultural landscapes around the world.

25 Large uncertainties arise when the reflectance encoded by a pixel originates  
26 either from a mixture of different land covers or from a single land cover with  
27 spatially heterogeneous properties. Intra-pixel spatial heterogeneity biases the  
28 estimation of land surface variables, such as LAI, when the relationship between  
29 this variable and the radiometric signal is non-linear (Friedl et al., 1995; Gar-  
30 rigues et al., 2006a). Geostatistics, and more precisely variograms, can be used  
31 to quantify landscape spatial heterogeneity from concurrent fine spatial resolu-

1 tion imagery (Garrigues et al., 2006b), providing the necessary information to  
2 correct the bias on the non-linear estimation of LAI (Garrigues et al., 2006a).  
3 The temporal changes in spatial heterogeneity can even be modelled to reduce  
4 the limitation of requiring concurrent imagery (Garrigues et al., 2008). Another  
5 approach for monitoring heterogeneous landscapes is to downscale coarse spa-  
6 tial resolution time series using unmixing-based data fusion (Zurita-Milla et al.,  
7 2009), thus creating fine spatial resolution synthetic images from which bio-  
8 physical variables can be retrieved. A common disadvantage of both methods  
9 (correcting the scaling bias and downscaling) is that they require a series of fine  
10 spatial resolution imagery, preferably during the increasing phase of LAI which  
11 unfortunately often coincides with the rainy season in many part of the world.  
12 Furthermore, modelling the spatial heterogeneity with these methods can be a  
13 complex issue, requiring serious approximations and *a priori* knowledge which  
14 might not be readily available for operational application.

15 Both above-mentioned approaches provide elegant solutions to deal with  
16 intra-pixel heterogeneity in order to provide a spatially exhaustive coverage of  
17 land surface variable estimations from coarse spatial resolution data. However,  
18 their sophistication potentially induces more approximation errors, which can  
19 be avoided if spatially continuous maps are not mandatory. Rather than using  
20 all the pixels in a scene, the analysis can be restricted to a subset of a region's  
21 pixels (Guissard et al., 2004; Kastens et al., 2005). Masking the cropland can  
22 significantly improve the accuracy of crop yield forecasts based on NDVI profiles  
23 (Genovese et al., 2001). But crop growth models are often specific to a given  
24 crop (or crop variety), and in order to couple them with remote sensing data  
25 it is preferable to use crop-specific masking. In some landscapes, like the north  
26 China plains, this is trivial since more than 90% of arable lands are covered by  
27 wheat during spring (Ren et al., 2008). Many landscapes are more fragmented:  
28 a crop specific field will be surrounded by other crops, and it is complicated to  
29 anticipate the patterns due to crop rotation. Furthermore, the size of a medium  
30 spatial resolution pixel is often, at best, of the same order of magnitude as  
31 the size of crop fields. In order to make proper use of medium resolution data

1 for crop growth monitoring, it is required to select pixels whose observational  
2 footprints fall within the target crop specific fields. A common misconception is  
3 that the observational footprint is the geometric projection of a rectangular pixel  
4 onto the Earth's surface (Cracknell, 1998). The footprint rather depends on the  
5 instrument's point spread function (PSF), which describes how the electromag-  
6 netic radiation coming from a point source is spread over the image plane as  
7 it is recorded by the imaging instrument. Duveiller & Defourny (2010) demon-  
8 strated how modelling the PSF and convolving it over a crop specific mask can  
9 yield a pixel purity map. This maps provides the crop specific pixel purity ( $\pi$ ),  
10 a variable defining the proportion of signal encoded in a pixel which originates  
11 from the targeted crop.

12 The objective of this paper is to demonstrate whether it is possible to es-  
13 timate both the spatial range and temporal dynamic of crop specific GAI at  
14 regional scale from medium spatial resolution data. Regional scale is here un-  
15 derstood as a situation when the extent of the geographic coverage should be  
16 national or sub-national and the elementary unit of interest is a small area with  
17 similar agro-ecological growing conditions (preferably with an administrative  
18 delineation in order to link results to official statistics). This paper targets the  
19 population of all fields of a given crop within one such area, in which GAI is  
20 expected to vary due to differences in soil types, management practices, crop  
21 varieties, etc. despite being subject to the similar local weather. The charac-  
22 terisation of the GAI of this population with medium resolution imagery will  
23 be achieved by controlling the adequacy between observation footprint and the  
24 targeted fields using pixel purity. The impact of the selection of pixel purity  
25 thresholds on the characterization of the regional GAI will first be studied. A  
26 second analysis will then focus on how the observation geometry can further  
27 be used to filter out GAI estimations of lower quality to improve the temporal  
28 consistency of the GAI profiles. Finally, the results are validated using GAI  
29 maps obtained from high spatial resolution imagery acquired at various dates  
30 along the growing season.

## 1 2. Study site and data

2 To achieve the above-mentioned objectives, both fine and coarse spatial  
3 resolution imagery needs to be available over a large agricultural landscape along  
4 the whole growing season. The chosen study site is  $40 \times 40$  km in size and is  
5 located in the Danube Plain, centred on Fundulea (Romania, around  $44.41^\circ$  N,  
6  $26.58^\circ$  E). This agricultural landscape is dominated by relatively large fields  
7 (15 to 40 ha) of winter cereals (wheat and barley) alternating with summer  
8 crops (such as maize and sunflower). In 2001, imagery over the study site was  
9 intensely collected by high spatial resolution SPOT satellites thanks to a project  
10 called ADAM (Assimilation of spatial Data within Agronomic Models), whose  
11 aim was to develop and evaluate methods capable of exploiting high spatial  
12 satellite observations to optimize cultural practices, estimate the production,  
13 and evaluate environment impacts (Baret et al., 2001). The SPOT imagery in  
14 the ADAM dataset<sup>1</sup> constitutes the high spatial resolution data used in this  
15 paper, while the coarse spatial resolution data are assured by MODIS imagery.

### 16 2.1. SPOT imagery

17 The imagery within the ADAM dataset is composed of a time series of  
18 cloud-free images acquired from the SPOT 1, 2 and 4 satellites. The two HRV  
19 (High Resolution Visible) instruments on-board of the SPOT 1 and 2 platforms  
20 measure radiance in the green, red and near-infrared domain (NIR). The two  
21 HRVIR (High Resolution Visible InfraRed) instruments on-board of the SPOT  
22 4 platform have an extra band which measures shortwave infrared wavelengths  
23 (SWIR). All images have a 20 m nominal ground sampling distance. The im-  
24 ages have been accurately calibrated both radiometrically and geometrically by  
25 CNES (Centre National d'Etudes Spatiales, Toulouse, France). Both top-of-  
26 atmosphere (TOA) and top-of-canopy (TOC) reflectance imagery are available,  
27 the atmospheric correction having been done with the SMAC model (Rahman

---

<sup>1</sup>All the data is available at <http://kalideos.cnes.fr/>

1 & Dedieu, 1994) using aerosol characteristics measured with an automated sun-  
2 photometer on the ground. For the present experiment, a subset of 16 TOC  
3 reflectance images are used. These are distributed along the winter wheat grow-  
4 ing season between DoY (day-of-year) 60 and DoY 180. Table 1 presents the  
5 characteristics of the selected images, including the type of instrument and ac-  
6 quisition geometry *i.e.* view zenith angles (VZA), sun zenith angles (SZA) and  
7 relative azimuth angles (RAA).

8 [Table 1 about here.]

## 9 2.2. MODIS imagery

10 MODIS provides observation in 36 spectral bands: 29 bands with a spatial  
11 resolution at nadir close to 1 km, 5 bands with a spatial resolution close to 500 m  
12 and 2 bands with a spatial resolution close to 250 m.<sup>2</sup> MODIS scans the Earth  
13 with a 2340 km swath, providing a global coverage every 1-2 days. MODIS data  
14 has the great advantage of being pre-processed, free and readily available to the  
15 scientific community from the NASA Distributed Active Archive Center<sup>3</sup>. The  
16 MODIS data used in this paper are the daily reflectance data at 250 m of spatial  
17 resolution for which 2 bands are available encoding reflectance respectively in  
18 the red and near-infrared spectral domains. This data are known as MOD09  
19 and are part of collection 5 products. These level 2 products are all stored in  
20 the same grid, known as the L2G grid (see Wolfe et al., 1998, for details). In  
21 this grid, the data is projected using a Sinusoidal projection with a specific  
22 spheroid (a sphere with a radius of 6371007.181 m), and is distributed by tiles  
23 of  $4800 \times 4800$  pixels.

24 MODIS has some specific observational characteristics (see figure 1) that  
25 must be taken into account when studying ground objects which are close to

---

<sup>2</sup>Although MODIS products are generally referred to as having 1 km, 500 m and 250 m spatial resolution, the actual values are smaller and correspond respectively to 30, 15 and 7.5 arcseconds of the spheroid.

<sup>3</sup><https://wist.echo.nasa.gov/api/>

1 the pixel size. MODIS is a whiskbroom scanner whose integration time as the  
2 rotating mirror scans the Earth is nearly a whole detector width (Schowengerdt,  
3 2007) causing much higher spatial inter-pixel correlation in the cross-track direc-  
4 tion than in the along-track direction. Furthermore, the MODIS pre-processing  
5 step of gridding, *i.e.* assigning an observation to a predefined system of grid,  
6 introduces a “pixel-shift” (Wolfe et al., 1998). This shift can be quantitatively  
7 described by the notion of “observation coverage” or *obscov* (Wolfe et al., 1998)  
8 which is a ratio between: (1) the intersection area between the nominal ob-  
9 servation and the grid cell; and (2) the nominal area of the observation. The  
10 distribution of *obscov* values across a tile varies with the revisit cycle (figure 2).  
11 Tan et al. (2006) used this *obscov* value, which is provided along with MODIS  
12 reflectance products, to show the impact that gridding artifacts may have on  
13 compositing and band-to-band registration of MODIS data. These problems  
14 are compounded by the large across-track scan angle range of MODIS which  
15 results in view zenith angles (VZA) that can reach 65°. As the view zenith an-  
16 gle increases, so does the surface observed by the detector. This jeopardizes the  
17 quality of MODIS data since: (i) consecutive scan lines overlap when the VZA is  
18 different from 0° (the so-called “bow-tie” effect (Wolfe et al., 2002)) causing dis-  
19 continuities of the latitude/longitude fields provided with the data (Khlopenkov  
20 & Trishchenko, 2008); and (ii) with a high VZA, individual observations cover  
21 several adjacent grid cells since the grid cell size is fixed throughout the im-  
22 age. Since the nominal area of the observation defining *obscov* increases with  
23 VZA, both variables are not independent. However they provide information  
24 at different levels. Depending on how the observations will be positioned with  
25 respect to the grid, some observations with high VZA have higher *obscov* than  
26 their neighbours and can therefore be considered as more reliable. Similarly,  
27 low VZA does not guarantee a good observation since its *obscov* may be lower  
28 than its neighbours. These patterns of pixel vicinity are displayed on figure 3  
29 for a 200 × 200 pixel zone near the study area.

30 [Figure 1 about here.]

1 [Figure 2 about here.]

2 [Figure 3 about here.]

### 3 **3. Methodology**

4 The necessary processing steps to prepare comparable GAI products from  
5 SPOT and MODIS imagery are henceforth described. The general flowchart in  
6 figure 4 may guide the reader throughout the following descriptions.

7 [Figure 4 about here.]

#### 8 *3.1. Creating a crop specific mask*

9 First and foremost, it is necessary to identify the target objects in the scene.  
10 This resumes to having a mask covering the area where the target crop, winter  
11 wheat, is to be found in the 2001 growing season. This information could come  
12 from various sources other than remote sensing: one could imagine an online  
13 vector database of the fields which would be updated by farmers after sowing.  
14 However, in this case the only possibility was to classify a set of high spatial  
15 resolution images available in the ADAM database. Since this is not the main  
16 concern of this study, the methodology used to create this crop mask is only  
17 briefly described below.

18 Five SPOT4 images that are well-distributed along the season were selected  
19 from the ADAM database to provide the necessary information to capture win-  
20 ter wheat phenology and discriminate it from other crops across the landscape.  
21 NDVI and NDWI are calculated for each image and grouped together in a syn-  
22 thetic 10-band image. This image is then segmented using the multiresolution  
23 segmentation algorithm (Baatz & Schäpe, 2000) implemented in Definiens De-  
24 veloper 7 software (Definiens, 2008). The resulting segments, or objects, group  
25 spatially-adjacent pixels which have similar trajectories for both vegetation in-  
26 dices over the 5 selected dates. Such multi-temporal segmentation techniques  
27 have been used successfully to isolate spatial entities exhibiting change (e.g. De-  
28 sclée et al., 2006; Duveiller et al., 2008; Bontemps et al., 2008). The segments

1 are then clustered into groups using an unsupervised classification technique  
2 (ISODATA), and these groups are then labelled manually based on visual inter-  
3 pretation and expert knowledge of the landscape.

### 4 *3.2. Neural network GAI retrieval*

5 In this paper, GAI is retrieved from multispectral reflectance using neural  
6 network techniques (NNT) trained over canopy radiative transfer simulations.  
7 This hybrid approach combines advantages of statistical and physical approaches  
8 in biophysical variable retrieval (Dorigo et al., 2007; Baret & Buis, 2008). The  
9 approach is based on the algorithm conceived by Baret et al. (2007) to derive  
10 the global LAI product developed within the CYCLOPES (Carbon cYcle and  
11 Change in Land Observational Products from an Ensemble of Satellites) project  
12 from SPOT/VEGETATION data. The radiative transfer model used is PRO-  
13 SAIL (Baret et al., 1992), a coupling of the canopy reflectance model SAIL  
14 (Verhoef, 1984) to the leaf optical properties model PROSPECT (Jacquemoud  
15 & Baret, 1990). The CYCLOPES algorithm was later adapted for winter wheat  
16 GAI retrieval from the SPOT/HRV(IR) imagery in the ADAM database by  
17 Duveiller et al. (2011). This adaptation consisted in: (i) changing the number  
18 of neurons with respect to the change in different input bands; (ii) using the  
19 appropriate spectral response curves for the HRV and HRVIR instruments; and  
20 (iii) using a characterisation of the soil background reflectance specific to Fund-  
21 ulaire<sup>4</sup>. The same method was used here to derive GAI maps from SPOT imagery  
22 and the method was also adapted to retrieve GAI from MODIS reflectance in  
23 the red and near-infrared domains. Back-propagation neural networks with two  
24 hidden layers of respectively 5 and 1 neurons are employed. The required input  
25 values are VZA, SZA, RAA and the top of canopy reflectance in the different  
26 bands. Further description on the construction, training and performance of

---

<sup>4</sup>Note that the change from LAI in CYCLOPES to GAI in Duveiller et al. (2011) is just a question of terminology since the green elements modelled in PROSAIL can be considered to be approximations of either leaves, stems of ears as long as these are green

1 the neural networks can be found in Duveiller et al. (2011).

### 2 3.3. Modelling the spatial response of MODIS

3 Since the aim is to compare GAI retrieved from instruments with different  
4 spatial resolution, it is necessary to ensure that the observation footprints of  
5 both products coincide. Given the large difference in scale between the SPOT  
6 and MODIS support, the observation footprint of SPOT can be assumed to be  
7 equivalent to the square projection of the pixel. However, due to the complex  
8 acquisition system of MODIS, the spatial response of the coarse instrument  
9 cannot be neglected.

10 Having a measure of the spatial response of an instrument in orbit is not  
11 easy. Although it is measured in a laboratory under controlled conditions before  
12 launching the orbiting platform, there is the possibility for change in a system's  
13 PSF after launch due to thermal focus change or instrument outgassing in the  
14 space environment (Schowengerdt, 2007). Some techniques can be used to mea-  
15 sure the on-board PSF based on specific ground targets in the imagery ((*e.g.*  
16 Ruiz & Lopez, 2002)). However, for instruments such as MODIS, the spatial  
17 resolution is often too coarse to find appropriate targets and synchronized high  
18 spatial resolution imagery might be required (*e.g.* Rojas et al., 2002). MODIS  
19 is equipped with a Spectro-radiometric Calibration Assembly (SRCA) (Xiong  
20 & Barnes, 2006), which can measure and monitor the actual on-orbit modula-  
21 tion transfer function (MTF)<sup>5</sup>. Nevertheless, this measurement does not take  
22 into account the spatial response distortions caused by atmospheric effects. The  
23 impact of the spatial response on the imagery available to the user is further  
24 distorted pre-processing steps such as resampling.

25 Given the above-mentioned difficulties in measuring the spatial response,  
26 a general but conservative model is built for this study. The net instrument  
27 PSF can be modelled by taking into account its different components: the elec-

---

<sup>5</sup>The MTF is the counterpart of the PSF in the spatial frequency domain and characterizes the attenuation of the spatial frequencies by the imaging instrument

1 tronic PSF, the detector PSF, the image motion PSF and the optical PSF  
 2 (Schowengerdt, 2007). For the sake of simplicity the electronic components is  
 3 neglected. The detector is modelled by a uniform square pulse function:

$$PSF_{det}(x, y) = rect(x/\nu) \cdot rect(y/\nu) \quad (1)$$

4 where  $x$  and  $y$  are the spatial coordinates with their origin at the centroid  
 5 of the ground-projection of the detector's instantaneous field of view,  $\nu$  is the  
 6 detector width and  $rect(x/\nu)$  is the rectangular function (which is a square  
 7 pulse of amplitude one and width  $\nu$ ). While the along-track image motion can  
 8 be disregarded for MODIS, the across-track must be taken into account since  
 9 the integration time corresponding to image motion as the rotating mirror scans  
 10 the Earth is nearly a whole detector width (Schowengerdt, 2007). The detector  
 11 and image motion PSFs can be combined into a scan PSF:

$$PSF_{scan}(x, y) = PSF_{det}(x, y) * PSF_{IM}(x, y) \quad (2)$$

12 This scan PSF is modelled as a triangular PSF in the across-track direction<sup>6</sup>  
 13 and as a rectangular PSF in the along-track direction.  $PSF_{scan}$  must therefore  
 14 be inclined according to the angle,  $j$ , between the ground track of the satellite  
 15 and the north-south direction. This angle varies with the latitude,  $\varphi$ , according  
 16 to Capderou (2005):

$$j = \arctan \left[ \frac{\cos i - (1/\kappa) \cos^2 \varphi}{\sqrt{\cos^2 \varphi - \cos^2 i}} \right] \quad (3)$$

17 where  $\kappa$  is the satellite's daily recurrence frequency and  $i$  is the inclination angle  
 18 (*i.e.* the angle between the orbital plane and the equatorial plane). Finally, the  
 19 optical component is assumed to have a Gaussian behaviour

$$PSF_{opt}(x, y) = \exp \left( -\frac{x^2 + y^2}{2(\nu\sigma)^2} \right) \quad (4)$$

20 where  $\sigma$  is the standard deviation of the Gaussian curve. In this case  $\nu\sigma$  was  
 21 set to the plausible value of 50 m. The net PSF is a convolution of the scan

---

<sup>6</sup>Which is the along-scan direction for MODIS since it is a whisk-broom instrument.

1 PSF obtained in equation 2 with the optical PSF of equation 4 as illustrated in  
2 figure 5 and resumed by the following equation:

$$PSF_{net}(x, y) = PSF_{scan}(x, y) * PSF_{opt}(x, y) \quad (5)$$

3  $PSF_{net}$  is also depicted in 3 dimensions in figure 6. The corresponding MTF  
4 model was compared to the on-board MTF measurements provided MODIS  
5 Characterization Support Team. The result, shown in figure 7, indicate that  
6 the model provides a reasonable approximation. Furthermore it confirms that  
7 the value of 50 m for  $\sigma$  in  $PSF_{opt}$  is plausible since the modelled spatial response  
8 (the solid line) is close to the validation measurements (the crosses).

9 [Figure 5 about here.]

10 [Figure 6 about here.]

11 [Figure 7 about here.]

### 12 3.4. Convolution of the spatial response over the SPOT imagery

13 The next step to make the observation footprints of SPOT and MODIS coin-  
14 cide is to convolve the MODIS spatial response model over the SPOT products  
15 (the crop mask and the GAI maps). To do so, the  $PSF_{net}$  is discretized to 20  
16 m: the spatial resolution of the SPOT images. The change in support is then  
17 realized by applying a bi-dimensional convolution of the spatial response model  
18 over the target image  $Img$ :

$$\Pi_{Img}(x, y) = Img(x, y) * PSF_{net}(x, y). \quad (6)$$

19 Every pixel of the resulting image  $\Pi_{Img}(x, y)$  displays the value corresponding  
20 to a MODIS observation whose centroid falls at that  $(x, y)$  coordinate. When  
21 applied to the crop specific mask, the result is what will henceforth be referred  
22 to as a crop specific pixel purity map. This map indicates the purity of MODIS  
23 observations with respect to our target crop: winter wheat. When the convolu-  
24 tion is applied to the GAI maps, the resulting convolved maps indicate the GAI

1 that can be expected when estimated with a MODIS observation support. It  
2 must be acknowledged that this does not take into account the gridding effect  
3 that may occur when the MODIS observation is stored in the L2G grid.

### 4 3.5. Producing adequate MODIS time series

5 The last step consists in building GAI time series for an ensemble of points  
6 where MODIS crop specific pixel purity is above a certain threshold. Two types of  
7 time series are to be produced: (i) simulated MODIS GAI time series obtained  
8 from the convolved GAI maps produced from SPOT imagery ( $TS_{sim}$ ); and  
9 (ii) actual MODIS GAI time series obtained by retrieved GAI from MODIS  
10 reflectances ( $TS_{obs}$ ). While the latter contain GAI estimations obtained with  
11 variable observation geometry (*i.e.* VZA and *obskov*), the former are simulations  
12 of GAI obtained from MODIS in ideal conditions: that is at nadir and without  
13 gridding artifacts.

14 To identify the desired pixels in the L2G grid that must be used, the geolo-  
15 cation of their centroids in the MODIS sinusoidal projection is retained. These  
16 values are re-projected into the Gauss-Kruger projection in which the SPOT  
17 products within the ADAM database are projected. For each point, the corre-  
18 sponding MODIS purity is extracted from the crop specific pixel purity map.  
19 It must be acknowledged that this procedure for associating the purity to a cell  
20 in the L2G grid is an approximation because gridding artifacts are neglected  
21 (normally the centroid of the observation footprint is not going to be the same  
22 as the grid cell centroid). Pixel purity must therefore be taken as an indicator of  
23 the amount of interesting information present in the cell rather than an absolute  
24 measurement.

25 Since the main interest of this paper is time series dominated by wheat, only  
26 MODIS grid cells with at least 75% of purity are kept for the analyses. For these  
27 pure enough grid cells and for all available dates, the MODIS reflectances are  
28 transformed into GAI using a MODIS specific NNT to produce  $TS_{obs}$ . This set  
29 of time series also contains information on VZA and *obskov* for every individual  
30 MODIS acquisitions. To produce the other set of time series,  $TS_{sim}$ , GAI is

1 simply extracted from the convolved GAI maps for all selected grid cells in the  
2 same way as purity was obtained from the crop specific pixel purity maps.

### 3 3.6. Temporal smoothing

4 The SPOT high spatial resolution imagery do not necessarily coincide in  
5 time with the MODIS observations. In order to compare the GAI derived from  
6 both instruments, a canopy structural dynamic model (CSDM) can be used  
7 to smooth out one of the GAI estimation time series. The CSDM is a sim-  
8 ple semi-mechanistic model which describes the combined effect of growth and  
9 senescence with respect to thermal time by means of a mathematical expression.  
10 The CSDM both smooths the residual errors associated to each individual GAI  
11 estimation and describes continuously the biophysical variable's time course  
12 from a limited number of observations during the growth cycle (Koetz et al.,  
13 2005). In this study, a CSDM developed by Baret (1986) and improved by Lau-  
14 vernet (2005) is used, with the only difference that the biophysical variable is  
15 here labelled GAI instead of LAI. The mathematical expression is the following:

$$GAI(tt) = k \cdot \left[ \frac{1}{(1 + e^{-a(tt-T_0-T_a)})^c} - e^{b(tt-T_0-T_b)} \right] \quad (7)$$

16 where  $a$  and  $b$  define the rates of growth and senescence,  $c$  is a parameter  
17 allowing some plasticity to the shape of the curve,  $k$  is a scaling coefficient and  
18  $T_0$ ,  $T_a$  and  $T_b$  are the thermal times of plant emergence, mid-growth and end  
19 of senescence. The CSDM is further parametrized so as to yield zero GAI once  
20 senescence is finished.

21 The driving variable of the CSDM is thermal time ( $tt$ ) or cumulated growing  
22 degree-days. The thermal time for a single day  $tt_i$  is calculated in the following  
23 way:

$$tt_i = \left[ \frac{(T_{max} + T_{min})}{2} \right] - T_{base} \quad (8)$$

24 based on the daily minimum ( $T_{min}$ ) and maximum ( $T_{max}$ ) air temperatures  
25 recorded at the Fundulea meteo station.  $T_{base}$  is the temperature below which  
26 the process of interest, in this case winter wheat growth, does not progress. The

1 base temperature used here for winter wheat is 0°C and the starting date for the  
2 temperature sum is October 1st, 2000, which corresponds to the sowing period.

### 3 3.7. Statistical indicators

4 The following analyses will also require to quantify the correspondence be-  
5 tween GAI products. The discrepancies between a given product and a reference  
6 product will be compared using the statistical indicators presented in table 2.  
7 Amongst these,  $B$  and  $S$  are two subcomponents of the total discrepancy quan-  
8 tified by the  $RMSE$  and are related by the formula:  $RMSE^2 = B^2 + S^2$ .

9 [Table 2 about here.]

## 10 4. Results

11 The analysis of the data generated in this study is focused on answering  
12 three questions concerning GAI estimation from both fine and coarse spatial  
13 resolution.

### 14 4.1. How does pixel purity influence GAI regional estimation?

15 This question can be reasoned by analysing the bias that may occur between  
16 the median GAI obtained over all wheat fields in the region from fine spatial  
17 resolution and the median GAI obtained from coarse spatial resolution GAI  
18 estimations. This bias,  $\delta$ , is expected to occur because wheat GAI estimations  
19 from coarse spatial resolution can be contaminated by the signal from non-wheat  
20 surfaces located within the observation footprint. Therefore,  $\delta$  depends on the  
21 crop specific pixel purity threshold ( $\pi$ ) used to select a the population of coarse  
22 spatial resolution GAI estimates that will represent the regional estimation.

23 To analyse how  $\delta$  varies with  $\pi$  along the growing season, only the convolved  
24 and original GAI maps derived from SPOT are used. For every date in which  
25 there is a SPOT image, the median GAI of the region is calculated using all  
26 wheat pixels in the corresponding original GAI map.  $\delta$  is then calculated for

1 increasing values of  $\pi$  by subtracting the median GAI obtained from pixel pop-  
2 ulation of the convolved maps selected using the given threshold  $\pi$ . Figure 8  
3 describes the evolution of  $\delta$  with respect to  $\pi$  for the various dates at which  
4 GAI maps are available (the curves in figure 8 are actually 4th order polyno-  
5 mials fitted on punctual  $\delta$  values obtained with 100 discrete  $\pi$  values from 1 to  
6 100).

7 [Figure 8 about here.]

8 Figure 8 clearly shows how the  $\pi$  values used to select GAI estimations from  
9 the convolved maps have an effect on how well these estimations represent the  
10 median regional GAI obtained from the original GAI maps. Both the magnitude  
11 and the direction of this effect varies along the growing season. Early in the  
12 season (dark curves on figure 8) the bias is practically close to zero for all values  
13 of  $\pi$  because GAI values are low overall and there is little difference between  
14 the target (winter wheat) and non-target surfaces (mostly other crops). Later  
15 in the season, the winter wheat has higher GAI than neighbouring surfaces and  
16 thus, selections of “purer” pixels (higher  $\pi$ ) are necessary to limit the contami-  
17 nation effect from non-wheat surfaces which would bring down the median GAI  
18 estimation (thereby increasing  $\delta$ ). Late in the season (light curves on figure 8),  
19 summer crops surrounding the target winter wheat fields have a higher GAI,  
20 and therefore  $\delta$  takes negative values when  $\pi$  is low and contamination occurs.  
21 Overall there is a convergence towards  $\delta = 0$  when purity thresholds increase: a  
22 high  $\pi$  threshold will generally result in a smaller  $|\delta|$  by favouring observations  
23 which are more dominated with the target crop<sup>7</sup>. This illustrates the impor-  
24 tance of pixel purity on the regional GAI estimation. The convergence of the  
25 curves in figure 8 also indicates that the GAI retrieval algorithm is not really  
26 scale dependent for the considered spatial resolutions.

---

<sup>7</sup>Note, however, that if  $\pi$  is too restrictive and the reduction of selected pixels is too severe, the pixel selection might not be representative of the median GAI across the study area any more, thereby causing an increase in  $|\delta|$

1 The minimum pixel purity requirements to study the landscape can be de-  
2 fined by fixing a  $|\delta|$  which can be considered as acceptable. To illustrate how  
3 this minimum acceptable pixel purity is temporally dependent along the win-  
4 ter wheat growing season, the  $\pi$  values at which the curves in figure 8 reach  
5  $|\delta| = 0.10$  and  $|\delta| = 0.05$  are displayed on the top panel of figure 9. Since it  
6 is inconvenient to change the pixel purity thresholds along the season (because  
7 this creates gaps in the time series), it is more practical to know the potential  
8 bias that can occur with a fixed pixel purity threshold and how this bias evolves  
9 along the season. This is illustrated on the bottom panel of figure 9 for different  
10  $\pi$  thresholds.

11 [Figure 9 about here.]

#### 12 4.2. Can MODIS acquisition information be used to improve GAI estimation?

13 The GAI upscaled from SPOT to MODIS resolution,  $TS_{sim}$ , is considered  
14 to be at nadir and does not suffer from *obscov* local variations. However, the  
15 real MODIS data are rarely at nadir and have variable *obscov*. To exploit  
16 all MODIS observations it is necessary to analyse the effect of these two vari-  
17 ables on the quality of the GAI estimation. This is done by comparing the  
18 two ensemble of time series:  $TS_{sim}$  and  $TS_{obs}$ . In order to analyse all MODIS  
19 observations within  $TS_{obs}$ , these are compared to  $TS_{sim}^{\hat{}}$ , the temporal inter-  
20 polation of  $TS_{sim}$  using the CSDM (Eq. 7). The effect of VZA and *obscov*  
21 thresholds is then analysed. For increasing thresholds of *obscov* and decreasing  
22 thresholds of VZA, selections of fewer, but presumably more reliable estima-  
23 tions are made. For each selection of points, statistical indicators are calculated  
24 by considering that  $TS_{sim}^{\hat{}}$  is the reference time series ( $z$  in equations in ta-  
25 ble 2) and  $TS_{obs}$  is the estimation ( $\hat{z}$  in equations in table 2). The result can  
26 be visualized in iso-contour plots to see the combined effect of thresholds on  
27 both VZA and *obscov* (see figure 10). These graphs reveal an interesting point:  
28 desirable points do not need to satisfy simultaneously the conditions for the  
29 two variables. In other words, if an observation has a favourable *obscov*, it can

1 have an unfavourable VZA (and vice versa) and still remain reliable. To illus-  
2 trate the potential improvement that can be achieved by taking into account  
3 *obscov* and VZA, the dataset  $Z$ , consisting of all individual GAI estimations  
4 in  $TS_{obs}$ , is stratified into different groups for which the concurrent  $TS_{obs}$  and  
5  $TS_{sim}$  are compared. The groups are based on a single threshold for each  
6 variable, defined so that if taken by itself, at least 30% of the points remain.  
7 This yields a maximum acceptable VZA of  $24^\circ$  and a minimum acceptable *ob-*  
8 *scov* of 0.36. Figure 11 shows how both individual thresholds significantly filter  
9 out sub-optimal estimations, and how combining them by retaining the union  
10 of both constraints ( $z_1 \subset Z : VZA \leq 24^\circ \cup obscov \geq 0.36$ ) rather than their in-  
11 tersection ( $z_2 \subset Z : VZA \leq 24^\circ \cap obscov \geq 0.36$ ), the amount of usable points  
12 increases by 20% of the total amount  $Z$ .

13 [Figure 10 about here.]

14 [Figure 11 about here.]

15 The thresholding on *obscov* and VZA is expected to improve the temporal  
16 consistency of MODIS estimates. To test this, the CSDM is fitted for all avail-  
17 able time series using all available points (*i.e.* without any restrictions on either  
18 VZA or *obscov*). This temporally-smoothed GAI estimation is used as a refer-  
19 ence, to which different sets of punctual GAI estimations are compared. The  
20 results in table 3 confirm that filtering<sup>8</sup> MODIS estimations by either satisfying  
21 a *obscov* or a VZA criteria improves the temporal consistency as shown by the  
22 reduction of RRMSE. This is not merely an effect of sample number reduction  
23 as when a random sample set of equal size is used (the group labelled  $z_3$  in  
24 table reftab:TempCons), the statistical indicators remain comparable to when  
25 all points are used. Furthermore, the comparison between  $z_1$  (union) and  $z_2$  (in-  
26 tersection) shows that although the temporal consistency is slightly improved

---

<sup>8</sup>The term filtering, *i.e.* removing unwanted observation, must not be confused with the smoothing operation done with the CSDM in which the objective is removing the errors on the observations.

1 for  $z_2$ , it comes at the expense of a serious reduction of observations per time  
2 series.

3 [Table 3 about here.]

4 The bias of all cases in table 3 is slightly negative. The reason is that the  
5 fitting of a CSDM will always bring values around the peak down. Subset  $z_1$   
6 actually shows a more negative bias. This value can be reduced by fitting a  
7 CSDM on these values only. This indicates that by filtering out bad values, the  
8 overall GAI estimates are lower.

#### 9 4.3. How do MODIS GAI estimations compare to high spatial resolution GAI?

10 The last question that must be addressed is how well do the MODIS GAI  
11 estimations in  $TS_{obs}$  relate to the original (non-convolved) GAI maps, and  
12 whether they can characterize the regional GAI variability and its temporal  
13 dynamic. Hereafter, only the temporally smoothed profile based on  $VZA \leq$   
14  $24^\circ \cup obscov \geq 0.36$  are used on the MODIS side. These are first compared  
15 to the punctual SPOT upscaled GAI estimations and the resulting statistical  
16 indicators are displayed in figure 12. As expected, the performance is related  
17 to the date of acquisition: GAI is harder to estimate when it reaches its peak  
18 value (*i.e.* on DoY 123). However, the bias between MODIS and SPOT fluctuates  
19 along the season revealing shortcomings of the GAI SPOT estimation  
20 with respect to the MODIS smoothed estimation. These might be explained  
21 by errors in SPOT radiometric pre-processing but also by an inadequacy of the  
22 retrieval algorithm to correctly take into account the differences in acquisition  
23 geometry in the SPOT time series<sup>9</sup>. This bias effect penalizes the performance  
24 indicated by the RMSE, and even more so for the relative RMSE (*e.g.* DoY  
25 = 76). However, the dispersion of the estimation characterized by  $CV$  remains  
26 relatively stable all along the season suggesting that the overall performance of  
27 the MODIS GAI is stable.

---

<sup>9</sup>Note that this kind of errors are also expected from the MODIS side but these are smoothed out in this case by the CSDM.

1 [Figure 12 about here.]

2 Pixel purity affects the performance as well. Figure 13 shows how the RMSE,  
3 its constitutive parts ( $B$  and  $S$ ) and the coefficient of variation ( $CV$ ) vary  
4 for increasing pixel purity thresholds. As purity increases, the bias generally  
5 becomes more positive while the dispersion decreases. The reduction of  $S$  is  
6 easily understandable given the reduction of surface heterogeneity that pixel  
7 purity assures. The change in  $B$  results from the fact that SPOT convoluted  
8 estimations have the footprint of an ideal at-nadir simulation without gridding  
9 artefacts while the footprint of the MODIS estimations is affected by *obscov* and  
10 VZA, and is therefore potentially more contaminated with non-wheat GAI when  
11  $\pi$  is low. For the same reasons as mentioned in section 4.1, more contamination  
12 (*i.e.* less purity) will result in lower GAI during the main growing season when  
13 wheat GAI is higher than the GAI of neighbouring surfaces.

14 [Figure 13 about here.]

15 The main objective of using MODIS is to provide crop specific GAI informa-  
16 tion at a regional level, *i.e.* the  $40 \times 40$  km study area. To do so, the ensemble  
17  $TS_{obs}$  over the study area will be compared to the distribution of all points in  
18 the fine spatial resolution GAI map falling within the winter wheat mask. As  
19 it has been mentioned above, there is bias between MODIS and SPOT GAI  
20 estimations which is variable according the time of acquisition of the SPOT im-  
21 agery. Since the objective here is to assess the performance of the GAI obtained  
22 from MODIS, and not from SPOT, the bias for each SPOT GAI map compared  
23 to the concurrent MODIS estimation is removed from the entire map prior to  
24 estimating the regional range of GAI. Figure 14 summarizes the comparison at  
25 regional level by showing the boxplots of the SPOT GAI distributions overlaid  
26 over the ensemble of MODIS time series above 85% of crop specific purity be-  
27 fore and after the bias correction. A visual assessment of the spatial correlation  
28 between the MODIS punctual GAI estimations and the corrected SPOT GAI  
29 maps is presented in figure 15. It reveals that the MODIS estimations not only

1 grasp the inter-field variability reasonably well, but they can also characterize  
2 more subtle intra-field spatial differences over the larger fields.

3 [Figure 14 about here.]

4 [Figure 15 about here.]

5 To further evaluate how representative the MODIS estimations are with re-  
6 spect to the regional behaviour of all fields, the bias correction between SPOT  
7 and MODIS is done based on pixels selected with various increasing  $\pi$  thresh-  
8 olds. Table 4 resumes the RMSE for the estimation of different percentiles of  
9 the regional GAI with different levels of purity. The RMSE between both es-  
10 timations of the median values is better for 85% purity than 95% suggesting  
11 that an overly harsh purity threshold might not be desirable to characterize the  
12 general GAI dynamic.

13 [Table 4 about here.]

## 14 5. Discussion

15 The results demonstrate that, by controlling pixel-target adequacy, it is pos-  
16 sible to characterize both the spatial range and temporal dynamics of crop  
17 specific GAI at a regional scale with coarse spatial resolution imagery. The dif-  
18 ference in performance between MODIS and fine spatial resolution to estimate  
19 the median GAI over the  $40 \times 40$  km study region can be reduced to an RMSE  
20 of  $0.053 \text{ m}^2/\text{m}^2$  by filtering in the spatial and temporal dimensions using ap-  
21 propriate thresholds on pixel purity, *obsco*v and VZA. These results confirm the  
22 robustness of the retrieval algorithm after training it over learning databases  
23 with the same radiative transfer parametrisation but applying it to different  
24 instruments. Furthermore, the MODIS GAI estimations are generally coherent  
25 with fine spatial resolution GAI maps at both inter-field and intra-field levels.

26 The proposed approach can be generalized to other medium spatial resolu-  
27 tion instruments. Demonstrating the methodology on MODIS was a choice to

1 reach a large spectrum of potential users since MODIS data are widely used  
2 due to its easy availability and free access for the Earth observation commu-  
3 nity. However, MODIS was also chosen to demonstrate the applicability of the  
4 methods to data acquired with a complex acquisition geometry (whiskbroom  
5 configuration, wide scan angle, triangular PSF). It must be recognized that the  
6 target-support adequacy problems addressed in this paper are largely due to  
7 the artefacts brought by the gridding of MODIS observations in a raster grid  
8 (Tan et al., 2006; Kristof & Pataki, 2009). VZA and *obscov* are used as prox-  
9 ies of the adequacy between observation support and target. An alternative to  
10 avoid this problem has been proposed by (Kristof & Pataki, 2009) in which they  
11 re-process the raw MODIS data and instead of assigning the reflectance value  
12 to a raster grid cell, they assign it to vectors describing the observation foot-  
13 prints. Although this approach is bound to provide reflectance of higher quality,  
14 it is much more complex and computationally expensive, hindering its opera-  
15 tional use. Our approach has the advantage of being applicable to standard  
16 “off-the-shelf” pre-processed MODIS products which are widely used in the sci-  
17 entific community. The approach proposed here could also be applied to MERIS  
18 since it has been shown that pushbroom instruments also have gridding arti-  
19 facts which should be taken into account when looking at multi-temporal pixel  
20 entities (Gomez-Chova et al., 2011). Concerning the relevance of deploying such  
21 effort to control the spatial response of instruments which are nearing the end  
22 of their expected lifetime, it can be argued that both MODIS and MERIS will  
23 retain a significant importance as a long term record. Furthermore, the opera-  
24 tional successor of MODIS instruments, the VIIRS instrument which will be  
25 onboard of the NPOESS satellite, will have a similar whiskbroom configuration  
26 and slightly coarser spatial resolution (Miller et al., 2006).

27 This experiment reveals that there is a bias between MODIS and SPOT GAI  
28 estimations that varies along the season, potentially indicating errors in the GAI  
29 derivation that may come from less accurate radiometric measurements of SPOT  
30 radiances as well as from the atmospheric correction or from the neural network  
31 biophysical algorithm. In this study, it was chosen to correct this bias based

1 on the temporal consistency of the GAI dynamic estimated by the instrument  
2 providing the highest observation repetitivity: MODIS. This is a fine illustra-  
3 tion of instrument complementarity whereby the high temporal resolution of  
4 Terra/MODIS assures the general trajectory and the high spatial resolution of  
5 SPOT/HRV(IR) could be used to estimate the local spatial heterogeneity of  
6 GAI. Such benefits of joint exploitation of data should be considered in design-  
7 ing future Earth observation missions. In this regards, much can be expected  
8 from the combination of the global coverage at 20 m every 5 days using Sentinel-  
9 2 platforms with the daily global coverage at 300 m of Sentinel-3. Before that, a  
10 better opportunity to combine high temporal repetitivity with high spatial reso-  
11 lution will come with the programmed PROBA-V satellite whose cameras allow  
12 the adquisition of data with 100 m spatial resolution approximately every 5 days  
13 and daily data at 300 m. Before these future missions become operational, GAI  
14 could be derived from wide swath imagery with high spatial resolution such as  
15 AWiFS or DMC using a similar neural network approach, and such GAI estima-  
16 tion could be used to asses the sub-pixel spatial heterogeneity of coarse spatial  
17 resolution GAI over large geographic coverages. A pre-requisite is to have an  
18 information on the spectral response of these instruments which unfortunately  
19 is not always simple to obtain.

20 Before extending the approach described here to other agricultural sites, it  
21 is necessary to consider some technical issues. For instance, the selection of  
22 thresholds for pixel purity, VZA and *obsconv* limits the number of available GAI  
23 estimations and ultimately impacts the accuracy of the overall result. It has  
24 been shown that a judicious thresholds on VZA and *obsconv* improves the tem-  
25 poral consistency of the estimations (section 4.2) while spatial filtering based  
26 on pixel purity is necessary to avoid affecting the regional GAI characterization  
27 (section 4.1). However, the threshold values proposed here should not neces-  
28 sarily be transposed to other study sites. The value of VZA and *obsconv* as  
29 proxies of target-observation adequacy will vary with landscape fragmentation  
30 and crop rotation. Instead threshold choices should be reasoned with respect to  
31 data availability (which is dependent on cloud coverage). In this respect, it has

1 been shown that using both VZA and *obscov* in a non-exclusive way enables  
2 to conserve more GAI estimations than combined exclusive thresholds without  
3 compromising the accuracy. Perhaps further improvements could be achieved  
4 by assigning non-binary weights depending on favourable VZA and *obscov* val-  
5 ues instead of thresholding. However, the problem is then to choose the values  
6 for these weights. Concerning the choice of pixel purity thresholds, the analy-  
7 sis in section 4.1 provides insight into how it has to be reasoned according to  
8 time window of interest. The values obtained for maximum tolerable thresh-  
9 olds are to be considered in relative terms, as their absolute values will vary  
10 according to the choice of the statistical test used, its parametrization and the  
11 sub-sampling protocol that is employed. The temporal variation of this pixel  
12 purity threshold may be explained based on the variability of temporal GAI tra-  
13 jectories within the crop-specific mask, explaining the necessity of higher purity  
14 thresholds around the mid-season when winter wheat fields are less synchronised  
15 between each other. Later in the season, winter wheat fields are all back to low  
16 GAI, but surrounding summer crops have higher GAI which will contaminate  
17 GAI estimations unless high pixel purity values are selected. Since it would  
18 not be practical to change the threshold along the season, it seems appropriate  
19 to choose one assuring a good performance over most of the time window of  
20 interest, *i.e.* the window which would be more suitable for assimilating GAI  
21 into crop growth models. An upper limit for purity threshold could also be nec-  
22 essary if sampling within the larger fields biases the regional GAI estimation.  
23 In some landscapes such bias has been shown not to be present (*e.g.* Guissard  
24 et al., 2004). Over the study site, the analysis in section 4.1 does not detect that  
25 higher purity thresholds such as 95% provide biased estimations of the regional  
26 GAI. However, the results in table 4 do indicate that an overly harsh purity  
27 threshold is less appropriate to correctly characterize the regional distribution.

28 The crop mask at fine spatial resolution is necessary to assure regional crop  
29 specific GAI estimation with MODIS. Constructing this mask will require fine  
30 spatial resolution imagery, which is precisely one of the drawbacks of the other  
31 methods to deal with heterogeneous surfaces: downscaling (Zurita-Milla et al.,

1 2009) and correcting the scaling bias (Garrigues et al., 2006a, 2008). However, to  
2 build a crop mask, imagery acquired at any time during the growing season will  
3 be useful whereas for the other approaches, the imagery should preferably fall  
4 when it GAI estimations are more critical, *i.e.* during the fast growing phase  
5 which often coincides with smaller acquisition success due to increased cloud  
6 cover. Another issue concerning the crop mask is that, throughout this study,  
7 it has been implicitly assumed that for the target crop intra-field and inter-field  
8 heterogeneity is much smaller than the heterogeneity between the target crop  
9 and other land cover types. In some agricultural landscapes, the differences  
10 might not be so important because there is much GAI variability within a same  
11 field, or because the crop is confounded with neighbouring vegetation. In such a  
12 case, the notion of crop specific pixel purity might have to be revisited, perhaps  
13 using a fuzzy mask instead of a crisp binary mask to characterize the landscape.

14 The methodology presented here also calls for a relatively detailed model of  
15 the spatial response of MODIS in order to calculate pixel purity. Is it necessary  
16 to take the PSF into account or could a simple aggregation of the crop mask to  
17 a 250 m square pixel could be enough? This latter option is equivalent to mod-  
18 elling only the detector PSF with a square-wave function. Studies have shown  
19 that this simplified approach has an impact on land cover characterization that  
20 can be controlled by using a finer estimation of the instrument's spatial response  
21 (Townshend et al., 2000; Huang et al., 2002). When seeking the coarsest ac-  
22 ceptable spatial resolution requirements for agricultural monitoring, Duveiller &  
23 Defourny (2010) found that these are systematically over-estimated when using  
24 a square PSF instead of a model composed of both optical and detector compo-  
25 nents of the instrument's spatial response. Of course, the impact of modelling  
26 correctly the PSF on pixel purity is particularly important when the size of the  
27 observed objects are close to the size of the observation footprint.

28 A final point of discussion needs to address the smoothing of GAI with the  
29 CSDM. It must be acknowledged that relating GAI growth and senescence ex-  
30 clusively to thermal time is a simplification since this dynamic can be strongly  
31 influenced by other factors such as nitrogen deficiency and pest attacks. How-

1 ever, it is very difficult to have enough *a priori* information on these other  
2 factors to take them into account over a large geographic extent using a more  
3 sophisticated crop growth model for instance. Taking a time frame based on  
4 temperature, one of the main drivers of plant physiological processes, is already  
5 a significant improvement compared to just measuring time in days which are  
6 much less relevant for the crops.

## 7 **6. Conclusion**

8 By taking winter wheat as an example, this paper demonstrates that crop  
9 specific GAI estimations retrieved from coarse spatial resolution imagery such  
10 as MODIS are adequate to characterize crop dynamics at a regional scale. To  
11 achieve this, it is necessary to control the degree at which the observation foot-  
12 prints of the coarse pixels fall within the crop-specific mask delineating the tar-  
13 get. This control is done by filtering out less reliable GAI estimations in both  
14 the spatial and temporal dimensions using thresholds on pixel purity, *obskov*  
15 and VZA which were determined for this study.

16 The experiment has also demonstrated the possibility to retrieve coherent  
17 GAI estimates from different data with different scales using the same technique  
18 involving radiative transfer modelling and neural networks. Some shortcomings  
19 of the retrieval do exist, as revealed by the variable bias between high and  
20 coarse spatial resolution estimates at the different studied dates. However, these  
21 deviations can be corrected in a fine example of instrument complementarity  
22 whereby the high temporal resolution assures the general GAI trajectory and the  
23 high spatial resolution can be used to estimate the local spatial heterogeneity.

24 The concern of assuring pixel-target adequacy, widely addressed in this pa-  
25 per, is not limited to GAI nor agricultural monitoring. The proposed approach  
26 could indeed be used for any other application in which the output can be based  
27 on a subset of pixel samples within the scene. Although technological improve-  
28 ments are bound to provide finer spatial resolution data with more frequent  
29 revisit times, pixel-target adequacy will remain important for various remote

1 sensing application because once the technology arrives, users will naturally be  
2 inclined to look closer, more frequently and with more detail.

### 3 **Acknowledgment**

4 This research was funded by the Belgian *Fond de la Recherche Scientifique*  
5 – *FNRS* by way of a PhD grant to the first author. The research also falls in  
6 the framework of the GLOBAM project which is financed by the Belgian Sci-  
7 entific Policy (BELSPO) with the STEREO II programme. The data used  
8 in this paper are part of the ADAM database made available by Kalideos  
9 (<http://kalideos.cnes.fr>) and the SPOT imagery have the following copyright:  
10 CNES 2001 - Distribution Spot Image. The authors would like to thank Jim  
11 Tucker, Jean-Francois Ledent, Patrick Bogaert and the four anonymous review-  
12 ers for their comments and suggestions which have contributed to improve sig-  
13 nificantly this document. The authors also thank the MODIS Characterization  
14 Support Team (MCST) for providing specific details of the MODIS PSF.

15 Baatz, M. & Schäpe, A. (2000). Multiresolution Segmentation - an optimiza-  
16 tion approach for high quality multi-scale image segmentation, in Strobl, J.,  
17 Blaschke, T., & Griesebner, G., eds., *Angewandte Geographische Informa-*  
18 *tionsverarbeitung XII*, (pp. 12–23), Wichmann-Verlag, Heidelberg

19 Baret, F. (1986). *Contribution au suivi radiométrique de cultures de céréales*,  
20 Ph.D. thesis, Université de Paris-Sud

21 Baret, F. & Buis, S. (2008). *Advances in Land Remote Sensing. System, Model-*  
22 *ing, Inversion and Application*, chap. Estimating canopy characteristics from  
23 remote sensing observations. Review of methods and associated problems,  
24 (pp. 173–201), Springer Netherlands

25 Baret, F., Hagolle, O., Geiger, B., Bicheron, P., Miras, B., Huc, M., Berth-  
26 elot, B., Nino, F., Weiss, M., Samain, O., Roujean, J. L., & Leroy, M. (2007).

- 1 LAI, fAPAR and fCover CYCLOPES global products derived from VEGETA-  
2 TION: Part 1: Principles of the algorithm, *Remote Sensing of Environment*,  
3 *110* (3), 275–286
- 4 Baret, F., Jacquemoud, S., Guyot, G., & Leprieur, C. (1992). Modeled Anal-  
5 ysis of the Biophysical Nature of Spectral Shifts and Comparison With  
6 Information-content of Broad Bands, *Remote Sensing of Environment*, *41* (2-  
7 3), 133–142
- 8 Baret, F., Vintila, R., Lazar, C., Rochdi, N., Prevot, L., Favard, J. C., Bois-  
9 sezon, H. d., Lauvernet, C., Petcu, E., Petcu, G., Voicu, P., Denux, J. P.,  
10 Poenaru, V., Marloie, O., Simota, C., Radnea, C., Turnea, D., Cabot, F., &  
11 Henry, P. (2001). The ADAM database and its potential to investigate high  
12 temporal sampling acquisition at high spatial resolution for the monitoring of  
13 agricultural crops., *Romanian Agricultural Research*, (No.16), 69–80
- 14 Bontemps, S., Bogaert, P., Titeux, N., & Defourny, P. (2008). An object-based  
15 change detection method accounting for temporal dependences in time series  
16 with medium to coarse spatial resolution, *Remote Sensing of Environment*,  
17 *112* (6), 3181–3191
- 18 Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M. H., Ruget, F., Nicoullaud,  
19 B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., Richard, G.,  
20 Beaudoin, N., Recous, S., Tayot, X., Plenet, D., Cellier, P., Machet, J.-M.,  
21 Meynard, J. M., & Delécolle, R. (1998). STICS: a generic model for the  
22 simulation of crops and their water and nitrogen balances. I. Theory and  
23 parameterization applied to wheat and corn, *Agronomie*, *18* (5-6), 311–346
- 24 Capderou, M. (2005). *Satellites Orbits and Missions*, Springer Paris
- 25 Cayrol, P., Kergoat, L., Moulin, S., Dedieu, G., & Chehbouni, A. (2000). Cal-  
26 ibrating a Coupled SVAT-Vegetation Growth Model with Remotely Sensed  
27 Reflectance and Surface Temperature – A Case Study for the HAPEX-Sahel  
28 Grassland Sites, *Journal of Applied Meteorology*, *39* (12), 2452–2472

- 1 Chen, J. M. & Black, T. A. (1992). Defining leaf area index for non-flat leaves,  
2 *Plant, Cell and Environment*, 15 (4), 421–429
- 3 Cracknell, A. (1998). Synergy in remote sensing—What’s in a pixel?, *Internation-*  
4 *al Journal of Remote Sensing*, 19 (11), 2025–2047
- 5 Definiens (2008). *Definiens Developer 7 User Guide*, Definiens, Definiens AG  
6 Trappentreustr. 1 D-80339 München Germany, document version 7.0.5.968  
7 edn.
- 8 Deng, F., Chen, J., Plummer, S., Chen, M., & Pisek, J. (2006). Algorithm for  
9 Global Leaf Area Index Retrieval Using Satellite Imagery, *Geoscience and*  
10 *Remote Sensing, IEEE Transactions on*, 44 (8), 2219–2229
- 11 Desclée, B., Bogaert, P., & Defourny, P. (2006). Forest change detection by  
12 statistical object-based method, *Remote Sensing of Environment*, 102 (1-2),  
13 1–11
- 14 Dorigo, W., Zurita-Milla, R., de Wit, A., Brazile, J., Singh, R., & Schaep-  
15 man, M. (2007). A review on reflective remote sensing and data assimilation  
16 techniques for enhanced agroecosystem modeling, *International Journal of*  
17 *Applied Earth Observation and Geoinformation*, 9, 165–193
- 18 Duveiller, G. & Defourny, P. (2010). A conceptual framework to define the spa-  
19 tial resolution requirements for agricultural monitoring using remote sensing,  
20 *Remote Sensing of Environment*, 114 (11), 2637–2650
- 21 Duveiller, G., Defourny, P., Desclée, B., & Mayaux, P. (2008). Deforestation  
22 in Central Africa: Estimates at regional, national and landscape levels by  
23 advanced processing of systematically-distributed Landsat extracts, *Remote*  
24 *Sensing of Environment*, 112 (5), 1969–1981
- 25 Duveiller, G., Weiss, M., Baret, F., & Defourny, P. (2011). Retrieving wheat  
26 Green Area Index during the growing season from optical time series measure-  
27 ments based on neural network radiative transfer inversion, *Remote Sensing*  
28 *of Environment*, 115 (3), 887–896

- 1 Friedl, M., Davis, F., Michaelsen, J., & Moritz, M. (1995). Scaling and un-  
2 certainty in the relationship between the NDVI and land surface biophysical  
3 variables: an analysis using a scene simulation model and data from FIFE,  
4 *Remote Sensing of Environment*, 54, 233–246
- 5 Garrigues, S., Allard, D., & Baret, F. (2008). Modeling temporal changes in  
6 surface spatial heterogeneity over an agricultural site, *Remote Sensing of En-  
7 vironment*, 112 (2), 588–602
- 8 Garrigues, S., Allard, D., Baret, F., & Weiss, M. (2006a). Influence of landscape  
9 spatial heterogeneity on the non-linear estimation of leaf area index from mod-  
10 erate spatial resolution remote sensing data, *Remote Sensing of Environment*,  
11 105 (4), 286–298
- 12 Garrigues, S., Allard, D., Baret, F., & Weiss, M. (2006b). Quantifying spatial  
13 heterogeneity at the landscape scale using variogram models, *Remote Sensing  
14 of Environment*, 103 (1), 81–96
- 15 Genovese, G., Vignolles, C., Nègre, T., & Passera, G. (2001). A methodology  
16 for a combined use of normalised difference vegetation index and CORINE  
17 land cover data for crop yield monitoring and forecasting. A case study on  
18 Spain, *Agronomie*, 21, 91–111
- 19 Gomez-Chova, L., Zurita-Milla, R., Alonso, L., Amoros-Lopez, J., Guanter, L.,  
20 & Camps-Valls, G. (2011). Gridding Artifacts on Medium-Resolution Satellite  
21 Image Time Series: MERIS Case Study, *Geoscience and Remote Sensing*,  
22 *IEEE Transactions on*, PP (99), 1–11
- 23 Guissard, V., Defourny, P., & Ledent, J.-F. (2004). Crop specific information  
24 extraction based on coarse resolution pixel sampling, in *2nd VEGETATION  
25 Int. User Conf., Antwerp, Belgium, 2004*.
- 26 Huang, C., Townshend, J. R. G., Liang, S., Kalluri, S. N. V., & DeFries, R. S.  
27 (2002). Impact of sensor's point spread function on land cover characteriza-

- 1        tion: assessment and deconvolution, *Remote Sensing of Environment*, 80 (2),  
2        203–212
- 3        Jacquemoud, S. & Baret, F. (1990). PROSPECT: A model of leaf optical prop-  
4        erties spectra, *Remote Sensing of Environment*, 34 (2), 75–91
- 5        Kastens, J. H., Kastens, T. L., Kastens, D. L., Price, K. P., Martinko, E. A.,  
6        & Lee, R.-Y. (2005). Image masking for crop yield forecasting using AVHRR  
7        NDVI time series imagery, *Remote Sensing of Environment*, 99 (3), 341–356
- 8        Khlopenkov, K. & Trishchenko, A. (2008). Implementation and Evaluation  
9        of Concurrent Gradient Search Method for Reprojection of MODIS Level  
10        1B Imagery, *Geoscience and Remote Sensing, IEEE Transactions on DOI -*  
11        *10.1109/TGRS.2008.916633*, 46 (7), 2016–2027
- 12        Koetz, B., Baret, F., Poilve, H., & Hill, J. (2005). Use of coupled canopy struc-  
13        ture dynamic and radiative transfer models to estimate biophysical canopy  
14        characteristics, *Remote Sensing of Environment*, 95 (1), 115–124
- 15        Kristof, D. & Pataki, R. (2009). Tackling with the limitations of the raster data  
16        model: vector-based preprocessing of modis reflective bands, in Civco, D. L.,  
17        ed., *Fifth International Workshop on the Analysis of Multi-temporal Remote*  
18        *Sensing Images*, (pp. 160–167)
- 19        Lauvernet, C. (2005). *Assimilation variationnelle d'observations de télédétection*  
20        *dans les modèles de fonctionnement de la végétation : utilisation du modèle*  
21        *adjoint et prise en compte de contraintes spatiales.*, Ph.D. thesis, Université  
22        Joseph Fourier - Grenoble
- 23        Los, S., Pollack, N., Parris, M., Collatz, G., Tucker, C., Sellers, P., Malmstrom,  
24        C., DeFries, R., Bounoua, L., & Dazlich, D. (2000). A global 9-yr biophysical  
25        land surface dataset from NOAA AVHRR data, *Journal of Hydrometeorology*,  
26        1, 183–199

- 1 Masson, V., Champeaux, J.-L., Chauvin, F., Meriguet, C., & Lacaze, R. (2003).  
2 A Global Database of Land Surface Parameters at 1-km Resolution in Mete-  
3 orological and Climate Models, *Journal of Climate*, 16 (9), 1261–1282
- 4 Miller, S. D., Hawkins, J. D., Kent, J., Turk, F. J., Lee, T. F., Kuciauskas,  
5 A. P., Richardson, K., Wade, R., & Hoffman, C. (2006). NexSat: Previewing  
6 NPOESS/VIIRS Imagery Capabilities, *Bulletin of the American Meteorolog-  
7 ical Society*, 87 (4), 433–446
- 8 Moulin, S., Bondeau, A., & Delecolle, R. (1998). Combining agricultural crop  
9 models and satellite observations: from field to regional scales, *International  
10 Journal of Remote Sensing*, 19 (6), 1021–1036
- 11 Myneni, R. B., Hoffman, S., Knyazikhin, Y., Privette, J. L., Glassy, J., Tian,  
12 Y., Wang, Y., Song, X., Zhang, Y., Smith, G. R., Lotsch, A., Friedl, M.,  
13 Morisette, J. T., Votava, P., Nemani, R. R., & Running, S. W. (2002). Global  
14 products of vegetation leaf area and fraction absorbed PAR from year one of  
15 MODIS data, *Remote Sensing of Environment*, 83 (1-2), 214–231
- 16 Myneni, R. B., Maggion, S., Iaquinta, J., Privette, J. L., Gobron, N., Pinty, B.,  
17 Kimes, D. S., Verstraete, M. M., & Williams, D. L. (1995). Optical remote  
18 sensing of vegetation: Modeling, caveats, and algorithms, *Remote Sensing of  
19 Environment*, 51 (1), 169–188
- 20 Nieke, J., Frerick, J., Stroede, J., Mavrocordatos, C., & Berruti, B. (2008).  
21 Status of the optical payload and processor development of ESA's Sentinel  
22 3 mission, in *Proceedings of the IEEE International Geoscience & Remote  
23 Sensing Symposium, Jul. 2008., Boston, Massachusetts, U.S.A.*, vol. 4, (pp.  
24 145–153)
- 25 Rahman, H. & Dedieu, G. (1994). SMAC: a simplified method for the atmo-  
26 spheric correction of satellite measurements in the solar spectrum, *Interna-  
27 tional Journal of Remote Sensing*, 15 (1), 123–143

- 1 Rast, M., Bezy, J. L., & Bruzzi, S. (1999). The ESA Medium Resolution Imaging  
2 Spectrometer MERIS: a review of the instrument and its mission, *International*  
3 *Journal of Remote Sensing*, 20 (9), 1681–1702
- 4 Ren, J., Chen, Z., Zhou, Q., & Tang, H. (2008). Regional yield estimation for  
5 winter wheat with MODIS-NDVI data in Shandong, China, *International*  
6 *Journal of Applied Earth Observation and Geoinformation*, 10 (4), 403–413
- 7 Ritchie, T., J. & Otter, S. (1985). Description and performance of CERES-  
8 Wheat: a user-oriented wheat yield model, in *ARS Wheat Yield Project*, (pp.  
9 159–175), Natl. Technol. Info. Serv., Springfield, MI.
- 10 Rojas, F., Schowengerdt, R. A., & Biggar, S. F. (2002). Early results on the  
11 characterization of the Terra MODIS spatial response, *Remote Sensing of*  
12 *Environment*, 83 (1-2), 50–61
- 13 Ruiz, C. & Lopez, F. (2002). Restoring SPOT images using PSF-derived decon-  
14 volution filters, *International Journal of Remote Sensing*, 23, 2379–2391(13)
- 15 Salomonson, V., Barnes, W., Maymon, P., Montgomery, H., & Ostrow, H.  
16 (1989). MODIS: advanced facility instrument for studies of the Earth as  
17 a system, *Geoscience and Remote Sensing, IEEE Transactions on DOI -*  
18 *10.1109/36.20292*, 27 (2), 145–153
- 19 Schowengerdt (2007). *Remote sensing: models and methods for image process-*  
20 *ing*, San Diego: Academic Press., 3rd edn.
- 21 Sellers, P. J., Tucker, C. J., Collatz, G. J., Los, S. O., Justice, C. O., Dazlich,  
22 D. A., & Randall, D. A. (1994). A global 1° by 1° NDVI data set for climate  
23 studies. Part 2: The generation of global fields of terrestrial biophysical pa-  
24 rameters from the NDVI, *International Journal of Remote Sensing*, 15 (17),  
25 3519–3545
- 26 Tan, B., Woodcock, C., Hu, J., Zhang, P., Ozdogan, M., Huang, D., Yang, W.,  
27 Knyazikhin, Y., & Myneni, R. (2006). The impact of gridding artifacts on

- 1 the local spatial properties of MODIS data: Implications for validation, com-  
2 positing, and band-to-band registration across resolutions, *Remote Sensing of*  
3 *Environment*, 105 (2), 98–114
- 4 Townshend, J. R. G., Huang, C., Kalluri, S. N. V., Defries, R. S., Liang, S., &  
5 Yang, K. (2000). Beware of per-pixel characterization of land cover, *Internation-*  
6 *al Journal of Remote Sensing*, 21, 839–843(5)
- 7 van Diepen, C., Wolf, J., van Keulen, H., & Rappoldf, C. (1989). WOFOST: A  
8 simulation model of crop production., *Soil Use Management*, 5, 16–24
- 9 Verhoef, W. (1984). Light scattering by leaf layers with application to canopy  
10 reflectance modeling: The SAIL model, *Remote Sensing of Environment*,  
11 16 (2), 125–141
- 12 Wolfe, R. E., Nishihama, M., Fleig, A. J., Kuyper, J. A., Roy, D. P., Storey,  
13 J. C., & Patt, F. S. (2002). Achieving sub-pixel geolocation accuracy in sup-  
14 port of MODIS land science, *Remote Sensing of Environment*, 83 (1-2), 31–49
- 15 Wolfe, R. E., Roy, D. P., & Vermote, E. (1998). MODIS Land Data Storage,  
16 Gridding, and Compositing Methodology: Level 2 Grid, *Geoscience and Re-*  
17 *mote Sensing, IEEE Transactions on*, 36, 1324–1338
- 18 Xiong, X. & Barnes, W. (2006). *MODIS Calibration and Characterization*,  
19 chap. 5, (pp. 77–97), Springer Berlin Heidelberg
- 20 Zurita-Milla, R., Kaiser, G., Clevers, J., Schneider, W., & Schaepman, M.  
21 (2009). Downscaling time series of MERIS full resolution data to monitor veg-  
22 etation seasonal dynamics, *Remote Sensing of Environment*, 113 (9), 1874–  
23 1885

1	<b>List of Figures</b>	
2	1	Effects contributing to the MODIS spatial response . . . . . 37
3	2	Estimated probability density functions of observation coverage . 38
4	3	Spatial variations of observation coverage . . . . . 39
5	4	Flowchart . . . . . 40
6	5	Construction of the point spread function . . . . . 41
7	6	Model of the MODIS PSF . . . . . 42
8	7	Modelled spatial response and MTF measurements for MODIS . 43
9	8	Effect of $\pi$ on GAI regional estimation across the growing season 44
10	9	Evolution of minimum acceptable pixel purity and GAI bias along the growing season . . . . . 45
11		
12	10	Effect of thresholding on VZA and <i>obsconv</i> . . . . . 46
13	11	Filtering out sub-optimal estimations using VZA and <i>obsconv</i> thresh- olds . . . . . 47
14		
15	12	Performance of temporally smoothed MODIS GAI . . . . . 48
16	13	Performance of temporally smoothed MODIS GAI at different pixel purity values . . . . . 49
17		
18	14	Comparison of GAI time series from high and coarse spatial res- olutions . . . . . 50
19		
20	15	Visual assessment of the spatial correlation between SPOT and MODIS GAI . . . . . 51
21		

# Postprint

Version définitive du manuscrit publié dans / Final version of the manuscript published in : Remote Sensing of Environment, 2011, In Press. DOI : 10.1016/j.rse.2011.05.026

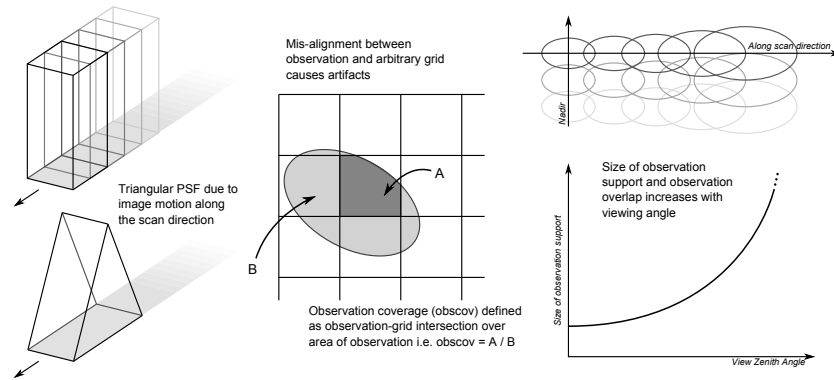


Figure 1: Effects contributing to the MODIS spatial response in the level 2 products: (left) the along scan image motion causes the squared detector point spread function (PSF) to become triangular when integrated during the time necessary to record one measurement; (centre) there is not a complete overlap between the observation footprint and the grid; and (right) the size of the observation support increases with the view zenith angle in the along scan direction.

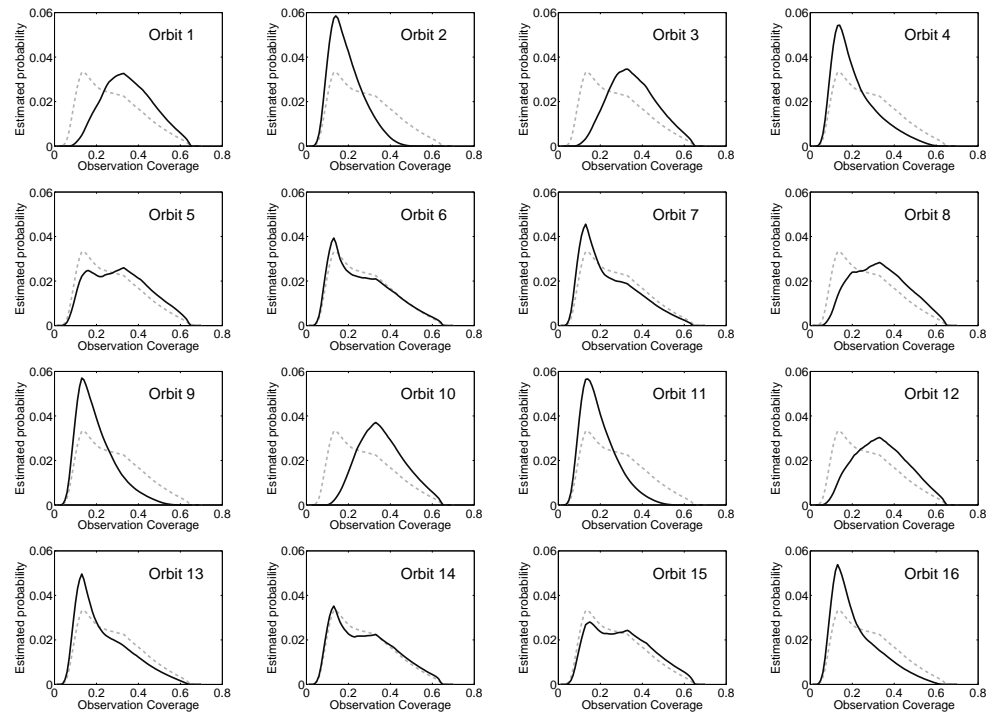


Figure 2: Estimated probability density functions of observation coverage (*obscov*) over the entire MODIS tile where the study site is located (tile H19V04) for each MODIS orbit. The sequence of the orbit numbers corresponds to the 16 consecutive days in the revisit cycle. On each subplot, the function of the given orbit (dark continuous line) can be compared to the mean observation coverage probability density function (light grey dashed line) covering the entire 16-day revisit cycle.

# Postprint

Version définitive du manuscrit publié dans / Final version of the manuscript published in : Remote Sensing of Environment, 2011, In Press. DOI : 10.1016/j.rse.2011.05.026

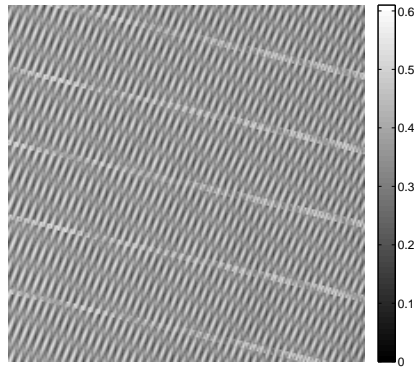


Figure 3: Example of the spatial variation of observation coverage (*obskov*) for a  $200 \times 200$  pixel area. The value of *obskov* is displayed according to the grey scale

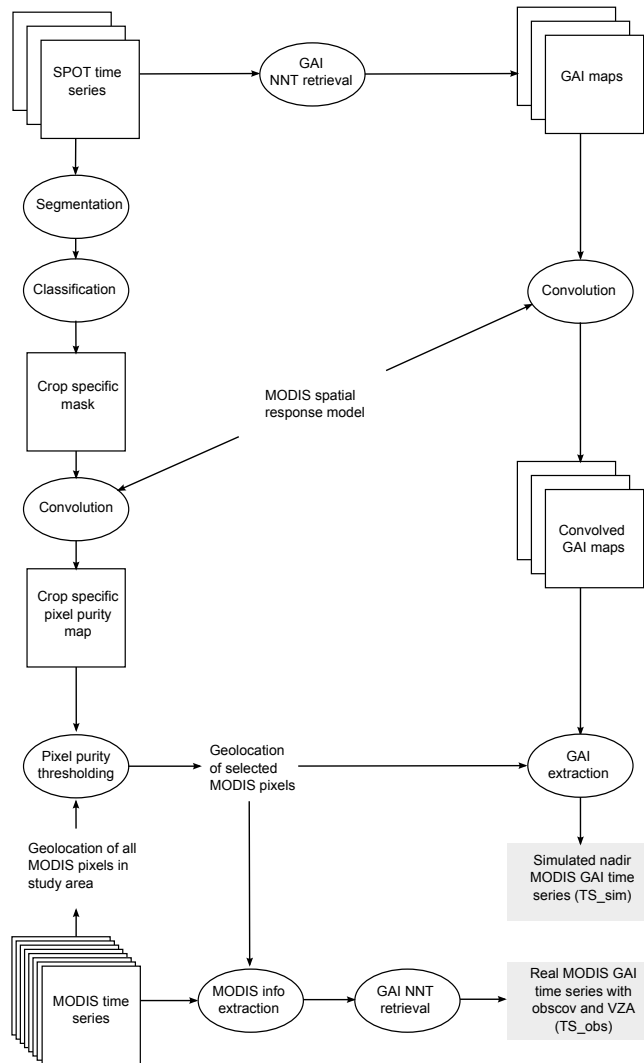


Figure 4: Flowchart to produce comparable GAI products from SPOT and MODIS imagery.

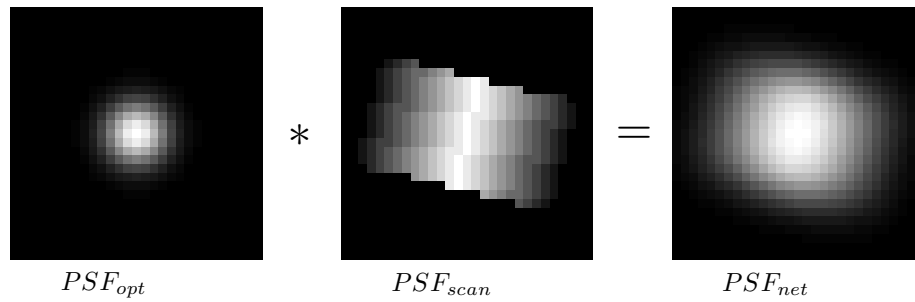


Figure 5: Schematic representation of the construction of the MODIS net point spread function based on the convolution of the optical with the scan PSF.

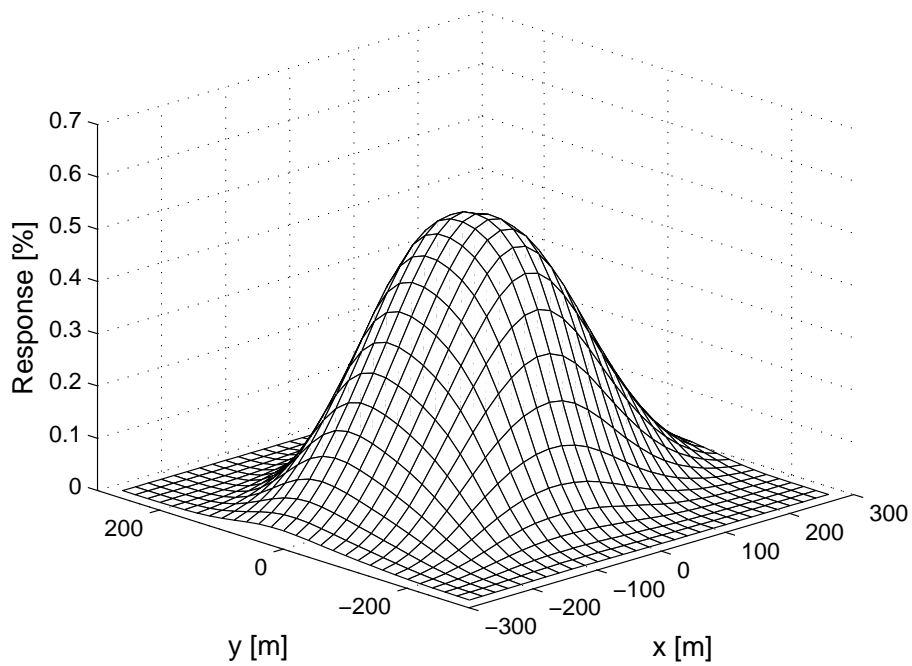


Figure 6: Spatial response (net point spread function) model of MODIS. Distances are calculated in meters from the centre of the observation footprint

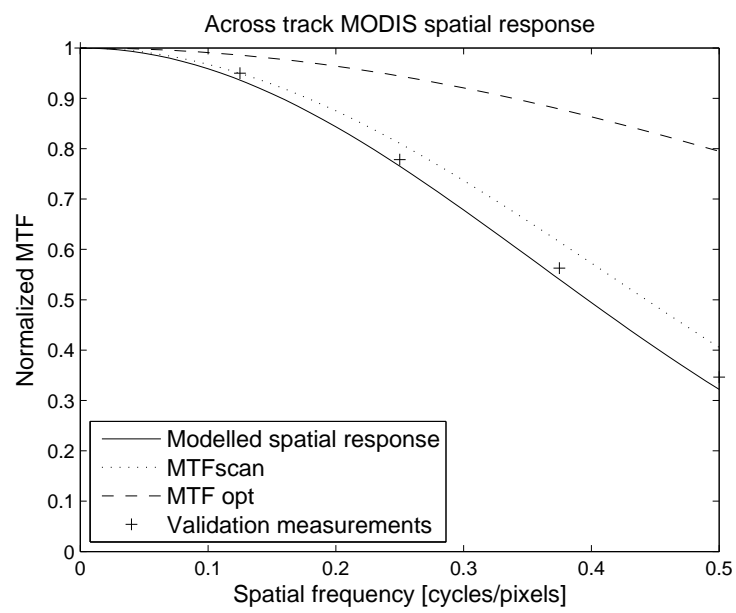


Figure 7: Comparison of the modelled spatial response of MODIS with MTF measurements realized by the MODIS calibration support team (<http://mcst.gsfc.nasa.gov/>).

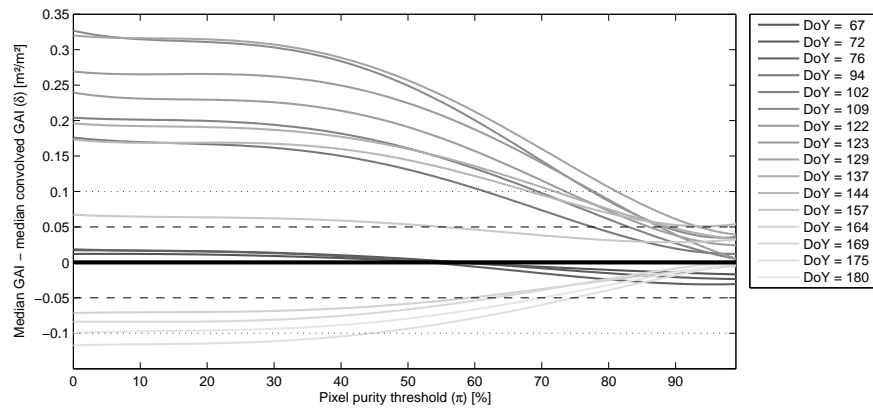


Figure 8: Effect of increasing pixel purity selection thresholds ( $\pi$ ) on the difference ( $\delta$ ) between median GAI from the original GAI maps and the convolved GAI maps for different dates (represented in increasingly lighter shades of grey).

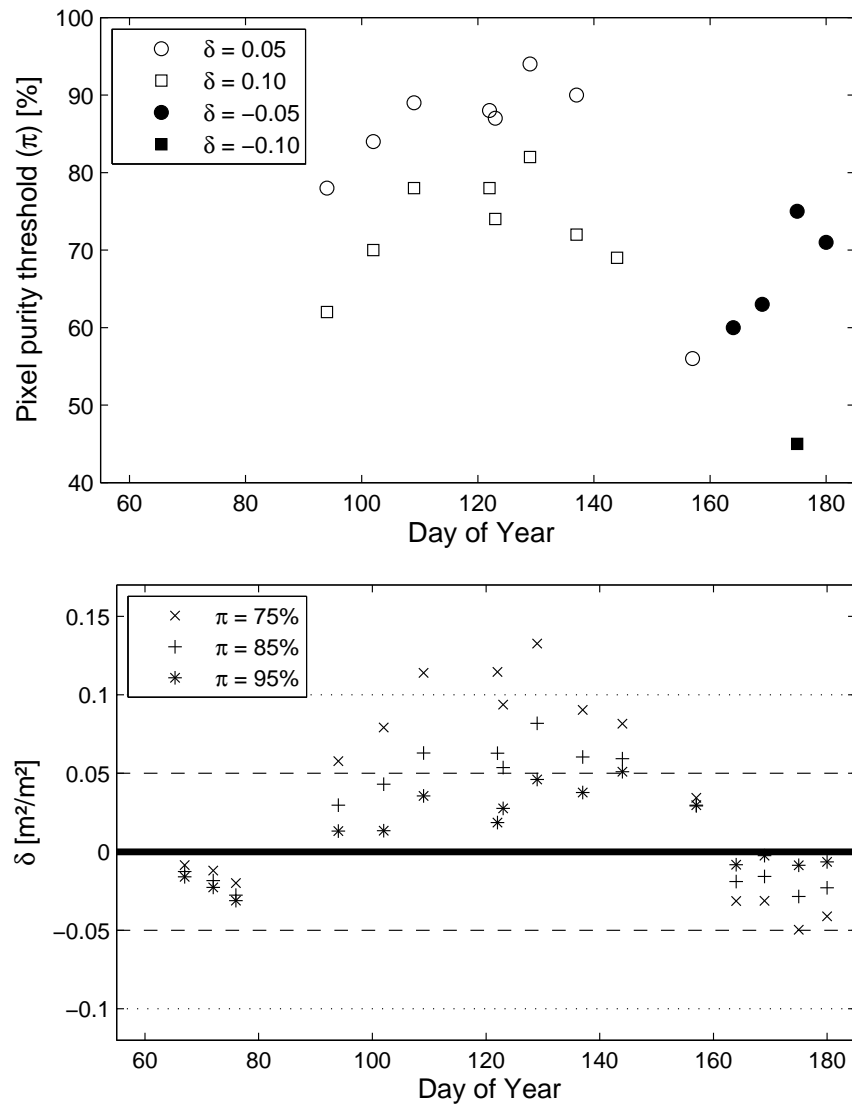


Figure 9: Evolution along the growing season of (top) the minimum acceptable pixel purity  $\pi$  and (bottom) the GAI bias  $\delta$  for a given set of fixed conditions of respectively  $\delta$  and  $\pi$ . Note that for the top figure, the number of points in each set can be different depending on the number of curves in figure 8 which cross the different  $\delta$  thresholds.

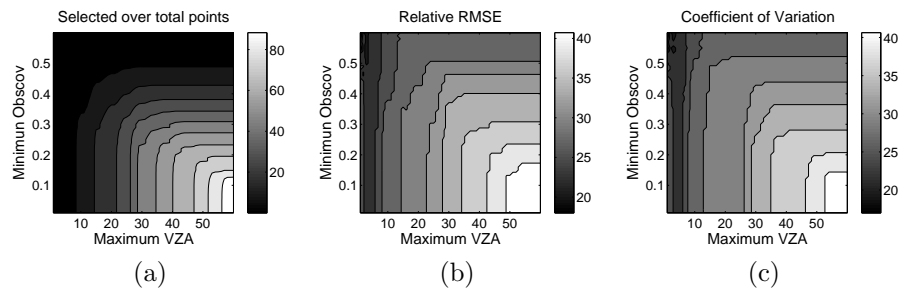


Figure 10: Combined effect of thresholds of a maximum VZA and a minimum *obskov* on (a) the percentage of estimations, (b) the relative RMSE and (c) the coefficient of variation between at nadir simulated MODIS time series and observed MODIS time series.

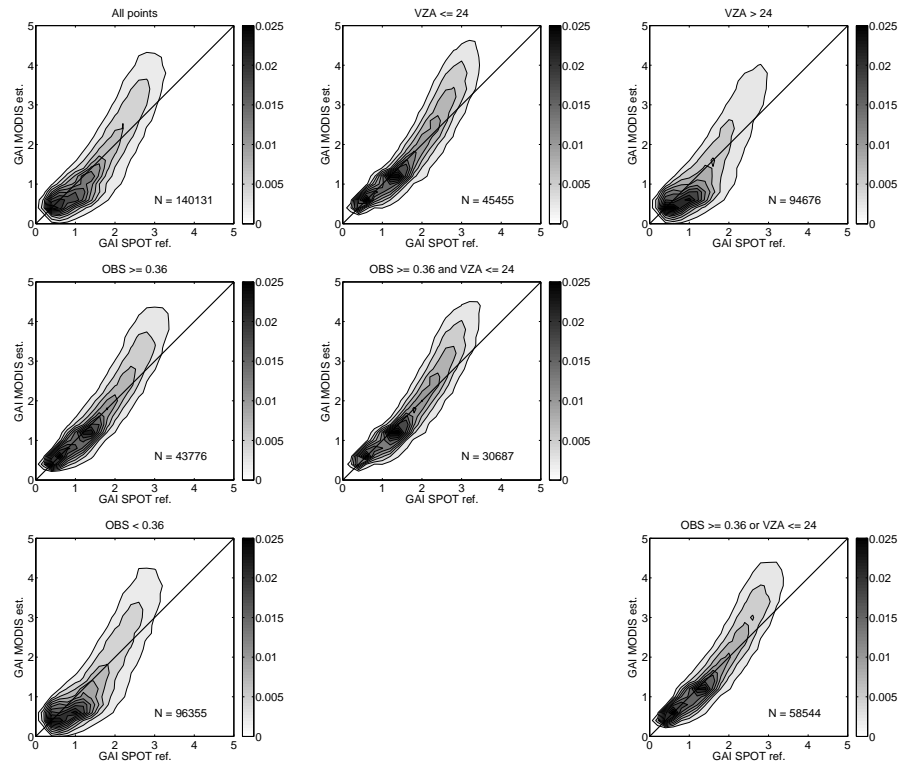


Figure 11: Comparison of the GAI values obtained from MODIS real values and temporally smoothed simulations of at nadir GAI based on SPOT high spatial resolution GAI maps. The contour plots of the 2-D distribution for all available points (top left) and for subsets according to VZA and *obsco*v thresholds indicated above the figures.

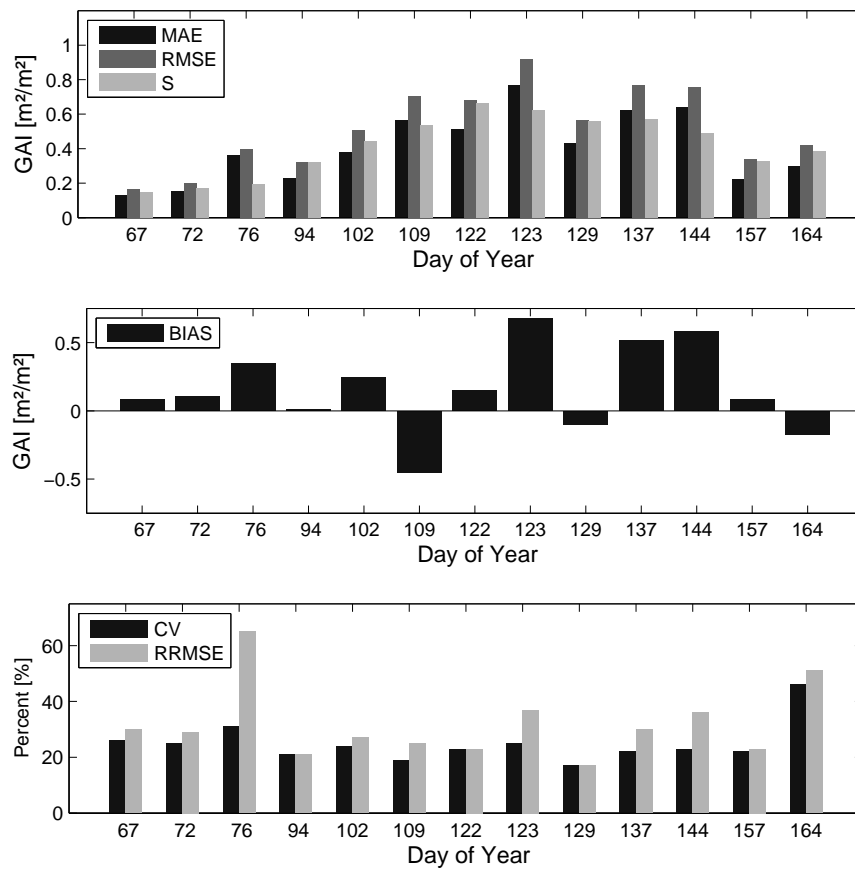


Figure 12: Statistical indicators comparing the performance of temporally smoothed MODIS GAI estimations against corresponding upscaled punctual SPOT GAI estimations. All MODIS points had a crop specific pixel purity ( $\pi$ ) above 75%. The bias indicates the difference of MODIS estimations minus SPOT estimations.

# Postprint

Version définitive du manuscrit publié dans / Final version of the manuscript published in : Remote Sensing of Environment, 2011, In press. DOI: 10.1016/j.rse.2011.05.

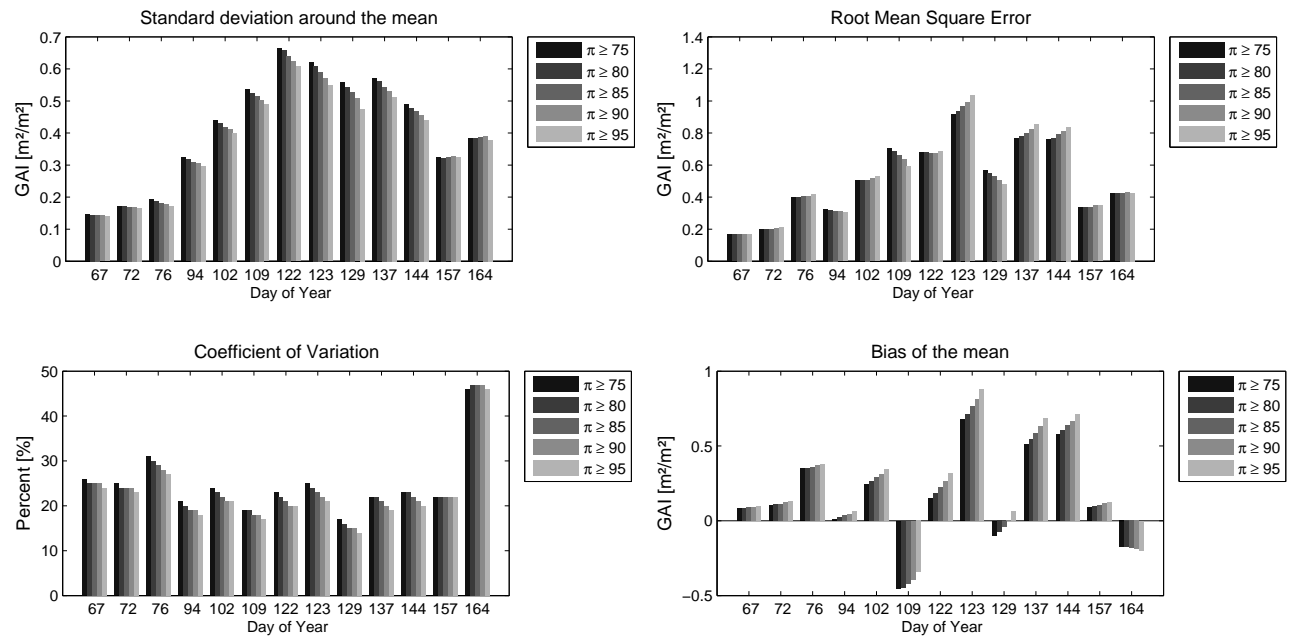


Figure 13: Statistical indicators comparing the performance of temporally smoothed MODIS GAI estimations against corresponding upscaled punctual SPOT GAI estimations for different pixel purity values

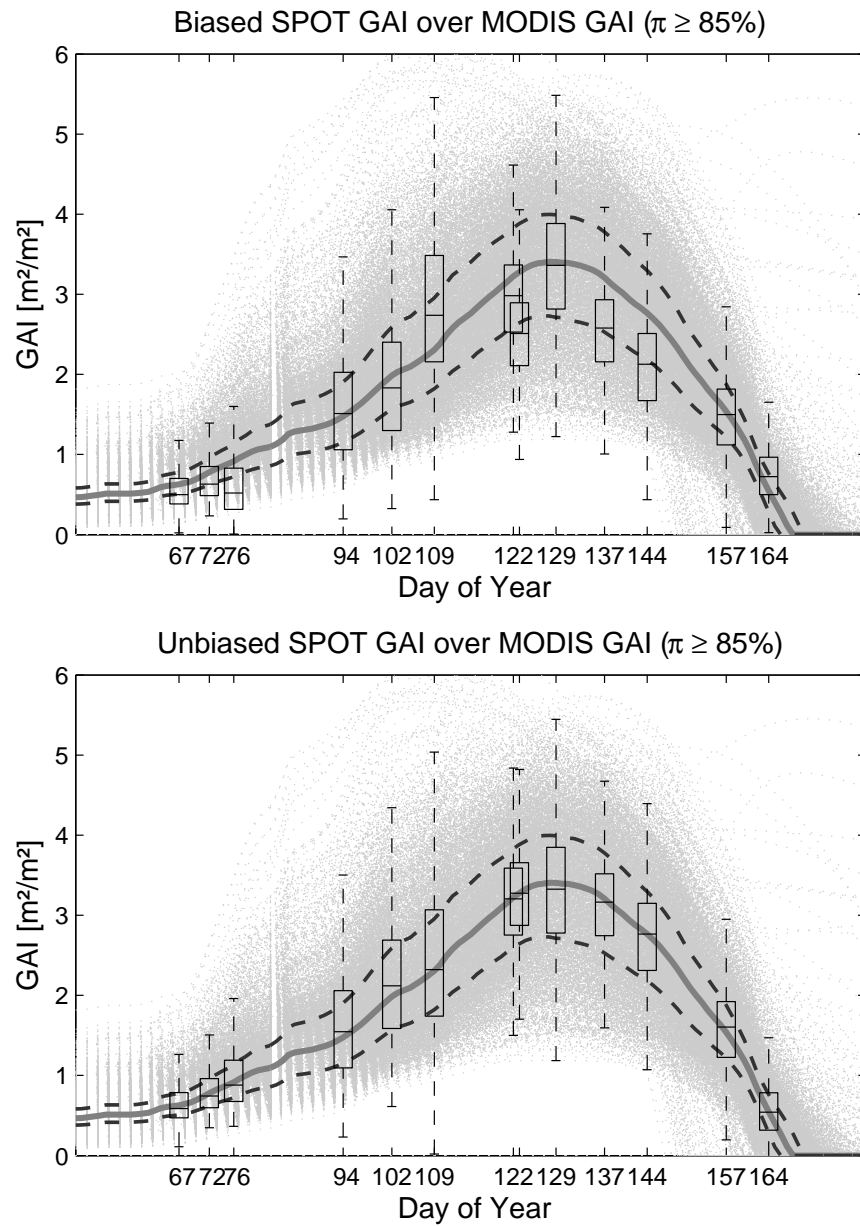


Figure 14: Boxplots of the SPOT GAI distributions overlaid over the ensemble of MODIS time series above 85% of crop specific purity. On top, the SPOT GAI distributions can be seen with their respective bias and on the bottom graph, the biased has been corrected. The solid line depicts the median value of MODIS time series, while the dashed lines represent the inter-quartile range (to be compared with the boxes).



Figure 15: Spatial comparison between high spatial resolution GAI maps from SPOT (in the background) with MODIS GAI estimations (dots) for 3 different  $7.2 \times 7.2$  km zones at the following days of year (from top to bottom): 76, 102, 123 and 144. The size of the dots relates to the pixel purity of the MODIS estimations, with larger dots being purer than smaller ones (only estimations above 75% pixel purity are shown). The images in the background are the respective Red channel of the original SPOT imagery used to derive the GAI maps.

# Postprint

Version définitive du manuscrit publié dans / Final version of the manuscript published in : Remote Sensing of Environment, 2011, In Press. DOI : 10.1016/j.rse.2011.05.026

## 1 List of Tables

2	1	Details of the SPOT imagery used in this study . . . . .	53
3	2	Statistics indicators and their definitions . . . . .	54
4	3	Effect that filtering out some GAI estimations has on temporal	
5		consistency of the GAI time series . . . . .	55
6	4	RMSE for the estimation of percentiles of GAI distributions with	
7		coarse spatial resolution . . . . .	56

Table 1: Details of the SPOT imagery used in this study to retrieve GAI. All images were acquired in 2001.

Date	DoY	Platform/Instrument	VZA	SZA	RAA
08-Mar	67	SPOT4/HRVIR2	19°	52.9°	-51.7°
13-Mar	72	SPOT4/HRVIR1	13°	50.7°	-52.5°
17-Mar	76	SPOT4/HRVIR2	19°	47.6°	-239.7°
04-Apr	94	SPOT2/HRV1	8°	41.6°	-52.7°
12-Apr	102	SPOT4/HRVIR1	20°	37.3°	-239.4°
19-Apr	109	SPOT4/HRVIR1	29°	37.3°	-45.2°
02-May	122	SPOT1/HRV1	20°	32.3°	-46.9°
03-May	123	SPOT4/HRVIR2	15°	30.3°	-236.5°
09-May	129	SPOT4/HRVIR2	8°	29.8°	-48.6°
17-May	137	SPOT1/HRV1	2°	27.5°	-49.8°
24-May	144	SPOT4/HRVIR2	9°	25.7°	-231.3°
06-Jun	157	SPOT1/HRV1	20°	23.2°	-234.3°
13-Jun	164	SPOT4/HRVIR2	30°	22.3°	-236.5°

Table 2: Statistics indicators and their definitions

Statistic	Formula
Mean Absolute Error	$MAE = \frac{1}{N} \sum_{i=1}^N  \hat{z}_i - z_i $
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (\hat{z}_i - z_i)^2}$
Bias	$B = \frac{1}{N} \sum_{i=1}^N \hat{z}_i - z_i$
Standard Deviation	$S = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{z}_i - z_i - B)^2}$
Relative Root Mean Square Error	$RRMSE = 100 \times \frac{RMSE}{\bar{z}}$
Coefficient of variation	$CV = 100 \times \frac{S}{\bar{z}}$

$N$ : number of observations;  $\hat{z}$ : satellite estimations

$z$ : ground measurements

$\bar{z}$ : mean value of the ground measurements

Table 3: Effect that filtering out some GAI estimations, from the entire available dataset  $Z$ , has on temporal consistency of the GAI time series. Temporal consistency is evaluated by comparing the selected values to the CSDM results. The different cases analysed here are: the union of *obsco*v and VZA constraints ( $z_1 \subset Z : VZA \leq 24^\circ \cup obscov \geq 0.36$ ), their intersection ( $z_2 \subset Z : VZA \leq 24^\circ \cap obscov \geq 0.36$ ) and a set of randomly selected individual GAI estimations ( $z_3$ ) with the same sample size as  $z_1$ .

Case	RMSE	RRMSE	B	S	$\bar{n}$
$Z$	0.514	30.9%	-0.013	0.521	30.3
$z_1$	0.433	23.6%	-0.084	0.420	13.2
$z_2$	0.413	22.4%	-0.055	0.397	7.1
$z_3$	0.504	30.6%	-0.014	0.510	13.2
$z_1^\dagger$	0.355	19.2%	-0.020	0.361	13.2

$\dagger$  CSDM fitted on  $z_1$  instead of on all  $Z$  points

Table 4: RMSE between the estimation of the percentiles of the high spatial resolution GAI distributions with the ensemble of coarse spatial resolution GAI time series when increasingly harsh levels of pixel purity are selected to threshold the latter. In bold is the lowest RMSE for estimating a given percentile.

Percentiles	Pixel purity threshold				
	75%	80%	85%	90%	95%
2.5%	<b>0.234</b>	0.241	0.253	0.278	0.282
25%	0.161	0.137	0.109	0.087	<b>0.079</b>
50%	0.077	0.059	<b>0.053</b>	0.064	0.083
75%	0.140	<b>0.139</b>	0.144	0.144	0.149
97.5%	0.365	<b>0.362</b>	0.364	0.366	0.369