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Performances of neural networks for deriving LAI estimates from existing CYCLOPES and MODIS products

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Abstract

This paper evaluates the performances of a neural network approach to estimate LAI from CYCLOPES and MODIS nadir normalized reflectance and LAI products. A data base was generated from these products over the BELMANIP sites during the 2001–2003 period. Data were aggregated at 3 km × 3 km, resampled at 1/16 days temporal frequency and filtered to reject outliers. VEGETATION and MODIS reflectances show very consistent values in the red, near infrared and short wave infrared bands. Neural networks were trained over part of this data base for each of the 6 MODIS biome classes to retrieve both MODIS and CYCLOPES LAI products.

Results show very good performances of neural networks to estimate the original LAI products with an overall root mean square error (RMSE) around 0.5 for MODIS LAI from both MODIS and CYCLOPES normalized reflectances and a RMSE ranging between 0.12 (CYCLOPES reflectances) and 0.29 (MODIS reflectances) for CYCLOPES LAI. A drop of 15% of performance was found by training MODIS biome dependant algorithm by a single network over all the classes at the same time. More detailed analyses show that CYCLOPES and MODIS LAI values are very consistent for grasses and crops. Conversely, other biomes including shrubs, savanna, needleleaf and broadleaf forests show significant discrepancies, mainly due to differences between LAI definitions used between CYCLOPES (closer to effective LAI) and MODIS (closer to true LAI). However, products derived from the original CYCLOPES LAI products show a better agreement with both effective and true LAI ground measurements values. MODIS LAI products show more instability, partly because of the slightly shorter temporal resolution as compared to CYCLOPES.

These results confirm the interest and versatility of neural networks for operational algorithms. This approach could be extended to other products or sensors, and may constitute a step forward for the fusion of data from several sensors, hence contributing to develop 'virtual constellations'.
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Keywords: Neural networks; LAI; CYCLOPES; MODIS; Consistency of products

1. Introduction

Leaf Area Index (LAI) is operationally estimated from remotely sensed optical imagery at global scale in the context of several international initiatives. Among those, National Aeronautics and Space Administration Moderate Resolution Imaging Spectroradiometer (NASA/MODIS) (Knyazikhin et al., 1998; Myneni et al., 2002) and European Union FP5 Carbon cYcle and Change in Land Observational Products from an Ensemble of Satellites (FP5/CYCLOPES) (Baret et al., 2007) LAI products are available freely to the user community. Other products derived from different sensors are in development and will be soon available, such as European Space Agency GLOBal land products for CARBON model assimilation (ESA/GLOBCARBON) (Plummer et al., 2006) or European organization for the exploration of METeorological SATellites Land Surface Analysis Satellite Application Facilities (EUMETSAT/LSA SAF) (García-Haro et al., 2005) LAI products.

From the application side, scientific and institutional users need validated products that should be consistent between sensors and associated with a good and known accuracy (Morisette et al., 2006). According to Global Climate Observation System (GCOS, 2006) the typical target accuracy required for LAI is

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around 0.5. However, recent validation studies have outlined significant discrepancies among several existing LAI products (e.g. Abuelgasim et al., 2006; Camacho-de Coca et al., 2006; Verger et al., 2006; Weiss et al., 2007). These results were used by the Committee for Earth Observation Satellite to state that none of the available LAI products are yet performing globally within the threshold requirements (CEOS, 2006).

To fully exploit the potential of current Earth observation programs and take advantage of the several products available, efforts have to be directed towards improving their consistency and accuracy. This needs validation and inter-comparison studies that are still very scarce (Baret et al., 2006). Parallel development of new strategies for fusion of sensor measurements and derived products is also required. Among the several approaches suited to relate sets of reflectances with the corresponding biophysical surface variables such as LAI, learning machine techniques such as neural networks (NNT) appear to be quite powerful and easy to implement operationally. They allow adjusting a surface response even over a complex and non-linear problem (Leshno et al., 1993; Krasnopolsky and Chevallier, 2003; Baret and Buis, 2007). NNT could thus be the basis of a generic 'unified' LAI estimation algorithm allowing to cover operationally, with algorithm specific tuning, a large range of sensors. NNT are increasingly used for the interpretation of remotely sensed data and the estimation of LAI (e.g. Danson et al., 2003; Fang and Liang, 2005; Bacour et al., 2006; Baret et al., 2007, Trombetti et al., 2008).

The objective of this paper is to evaluate the performances of neural networks when trained with the LAI product from one sensor and the reflectances from another. More specifically, MODIS (collection 4) and CYCLOPES (version 3.2) normalized reflectances and LAI products were considered. The four combinations between reflectance and LAI products from MODIS and CYCLOPES were investigated and their performances evaluated with regards to their consistency and accuracy as compared to those of the original MODIS and CYCLOPES LAI products.

In the first section, MODIS and CYCLOPES normalized reflectances and LAI products are described along with issues related to the spatial, temporal and spectral sampling. After comparing the original MODIS and CYCLOPES products, neural networks are described with emphasis on the learning process and data base. Performances of the proposed approach are then evaluated based on direct and indirect validation according to the methodology proposed by Weiss et al. (2007) for the validation of global LAI products. Finally, main conclusions and implications of findings are drawn.

2. Data and methods

2.1. CYCLOPES products

Version 3.2 of CYCLOPES products were used here. They are derived from VEGETATION sensor aboard SPOT4 and SPOT5 satellites (Henry, 1999). These products were downloaded from http://postel.mediasfrance.org. They correspond to 1/112° resolution (about 1 km at the equator) and are projected in plate-carrée. The radiometric calibration processes of VEGETATION data, cloud screening, atmospheric correction, Bidirectional Reflectance Distribution Function (BRDF) model inversion and LAI retrieval are described in Baret et al. (2007).

CYCLOPES normalized reflectances for nadir viewing are calculated using Roujean et al. (1992) BRDF model for the median solar zenith angle during the compositing period. Successive inversions allow rejecting observations disturbed by residual clouds and/or aerosols, as proposed by Hagolle et al. (2005). The temporal sampling interval is 10 days, and the temporal window over which observations are collected to adjust the BRDF model is 30 days, with Gaussian weighing that puts more emphasis on observations close to the centre of the window (Fig. 1).

Nadir viewing top of canopy reflectance in red, near infrared and middle infrared bands from VEGETATION sensors are input to the LAI algorithm along with the sun zenith angle. LAI values are computed by inverting the PROSPECT+SAIL radiative transfer model (Jacquemoud and Baret, 1990; Verhoef, 1984) using a biome independent neural network algorithm. CYCLOPES LAI product corresponds therefore to an effective LAI expected to be valid across all biomes. However, clumping at the landscape level (mixed pixels) is accounted for by assuming that each pixel is made of a Fraction of Vegetation Coverage (FVC) of pure vegetation and (1-FVC) of pure bare soil (Baret et al., 2007). Large ranges of values for canopy structure, leaf optical properties and background reflectance were used to generate the training data base that encompasses all biomes.

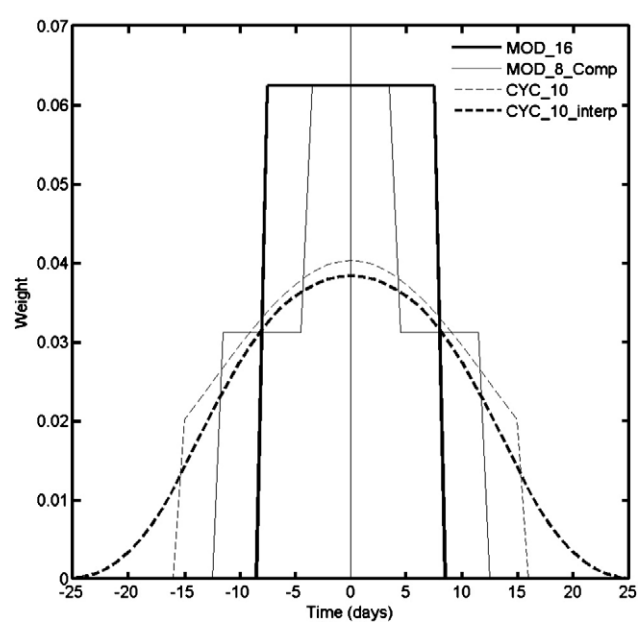

Fig. 1. Temporal resolution corresponding to the several products investigated. The temporal window is centred at day=0. MOD_16 corresponds to MODIS normalized reflectance products. MOD_8_Comp corresponds to the compositing of three consecutive original 8 days MODIS LAI product to get a closer temporal resolution to that of MOD_16. CYC_10 is the original temporal resolution of CYCLOPES products. CYC_10_interp corresponds to the average temporal resolution when interpolating CYCLOPES products at MOD_16 dates.

CYCLOPES LAI product was validated by Weiss et al. (2007) showing very good consistency with MODIS LAI seasonality, with however differences in magnitude but a better agreement with ground measurements.

2.2. MODIS products

MODIS collection 4 products were downloaded from http://edcdaac.usgs.gov. They correspond to a 1 km spatial resolution in a sinusoidal projection system.

MOD43B4 nadir BRDF-Adjusted Reflectance Product provides atmospherically corrected, cloud-free, normalized reflectance values for each of the MODIS land spectral bands (1–7, centred at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm, respectively) at the mean solar zenith angle of each 16 day period (Schaaf et al., 2002). MODIS atmospheric correction scheme is described in Vermote et al. (1997). The Ross-Li BRDF model (Lucht et al., 2000) with model parameters provided by MOD43B1 product is used to compute MOD43B4 product. In addition to the spectral nadir normalized reflectance values, the MOD43B4 product also provides extensive quality information.

MODIS LAI product (MOD15A2) is composited every 8 days using a main retrieval algorithm based on a three dimensional radiative transfer model tuned for six main biome classes (Knyazikhin et al., 1998). A Look-Up-Table (LUT) is used to compare observed and modeled red and near infrared daily BRFs for a suite of canopy structures, leaf optical properties and soil patterns that represent an expected range of typical conditions for a given biome type. LAI is retrieved as the mean value from all possible solutions within a specific level of input satellite data and model uncertainties. If this algorithm fails, a back-up procedure is triggered to estimate LAI from biome specific NDVI based relationships (Myneni et al., 1997).

MODIS global land cover type 3 (MOD12) yearly products are also used to provide the classification in six main biomes used in MOD15A2 LAI algorithm. Classification is derived from temporal profile features as observed during the year and includes: shrubs, savanna, grasses and cereal crops, broadleaf crops, needleleaf forest and broadleaf forest (Friedl et al., 2002).

Numerous validation experiments have quantified the reliability of MODIS MOD43 reflectance products (e.g. Jin et al., 2003), MOD12 land cover product (e.g. Cohen et al., 2006b) and MODIS LAI products (e.g. Wang et al., 2004; Tan et al.; 2005; Huemmrich et al., 2005; Cohen et al., 2006b). A summary of published validation efforts by multiple international teams is given in Yang et al. (2006).

2.3. Generation of a consistent data base

To properly implement the neural networks, a data base of CYCLOPES and MODIS normalized reflectances and LAI must be acquired over a globally representative ensemble of sites and over a time period long enough to show seasonal and interannual variability. The BELMANIP ensemble of sites is used, including 397 sites aiming at providing a good sampling of biome types and conditions over the globe (Baret et al., 2006). A three year period was considered, starting in 2001 and ending in 2003.

To allow NNT cross-learning and comparison between product performances, the data base is expected to reflect high degree of consistency over the spatial, temporal, spectral and directional dimensions of the signal.

Considering the spatial dimension, both CYCLOPES and MODIS products have approximately 1 km sampling interval while their projection systems differ. To achieve a comparison of both products over the same support area, the same projection system has to be used that should ideally keep the size of the sites independent from its location (Weiss et al., 2007). The MODIS sinusoidal projection system was selected because it ensures more consistency of the area of individual pixels between sites. CYCLOPES products were therefore reprojected into MODIS projection system using a bi-cubic resampling method (Reichenbach and Geng, 2003). To get similar spatial resolution and minimize the influence of geolocation uncertainties and point spread function, as well as to allow direct validation exercise, a 3 km × 3 km support area was considered for the analysis as recommended by Weiss et al. (2007). Because of the low quality of MODIS LAI back-up algorithm retrievals (Yang et al., 2006) mostly due to residual clouds and poor atmospheric correction (Wang et al., 2001), only the values retrieved with the main algorithm were selected to build the data base. To improve the homogeneity of the area and provide more consistent analysis per classes, we considered only the BELMANIP sites for which at least 5 pixels in the 3 km × 3 km area correspond to the dominant class, according to yearly MOD12 product. This class was finally assigned to each selected BELMANIP site. The median value over the 3 × 3 pixels area was computed when at least 5 high quality level pixels (not necessarilly the same) were available for each product. Using the median value instead of the average value of LAI and reflectances allows removing most outliers inside the 3 km × 3 km area. In addition, using the median makes a better match with the 'dominant class' if the class is assumed to be the main driver of variability between pixels in the 3 × 3 area.

For the temporal dimension, both resolution and sampling interval differ between MODIS, CYCLOPES LAI and normalized reflectance products. The lowest sampling frequency was selected as a reference, corresponding to the 16 days of MODIS normalized reflectance products. The 8 days original MODIS LAI products were thus composited to get about the same temporal resolution: the central 8 days value was averaged with the ones from the previous and the next compositing windows, assigning a 0.5 weight to these border observations. The central 16 days period therefore corresponds to 75% of the whole temporal window that spans over 24 days (Fig. 1). However, when one or two of the border observations were missing, the product was still computed from the remaining observations. Conversely, when the centre observation was missing, no product was computed. The CYCLOPES LAI and normalized reflectance products were interpolated at the central date of MODIS 16 days products if the two closest CYCLOPES products were within ±15 days from this date. The compositing window may thus vary between 40 and 60 days. The

contribution of the central 16 days period contributes on the average to 61% of the whole temporal window (Fig. 1). Despite these differences in temporal compositing, observations of LAI temporal evolution over situations showing high rate of change (Fig. 2, sites#2, #47 and #40) show very good consistency between products. This demonstrates that the differences in temporal compositing windows will have minor effects on the seasonality of products.

From the 27,790 observations potentially available at 16 days frequency for 3 years over the 397 sites, only 7572 matches i.e. 27% of the potential observations were finally considered after the spatial and temporal resampling and filtering process.

For the directional dimension, despite the fact that two distinct BRDF models are used for the normalization of CYCLOPES and MODIS reflectances, little differences are expected since time and geometry of observations are very close for both sensors (SPOT

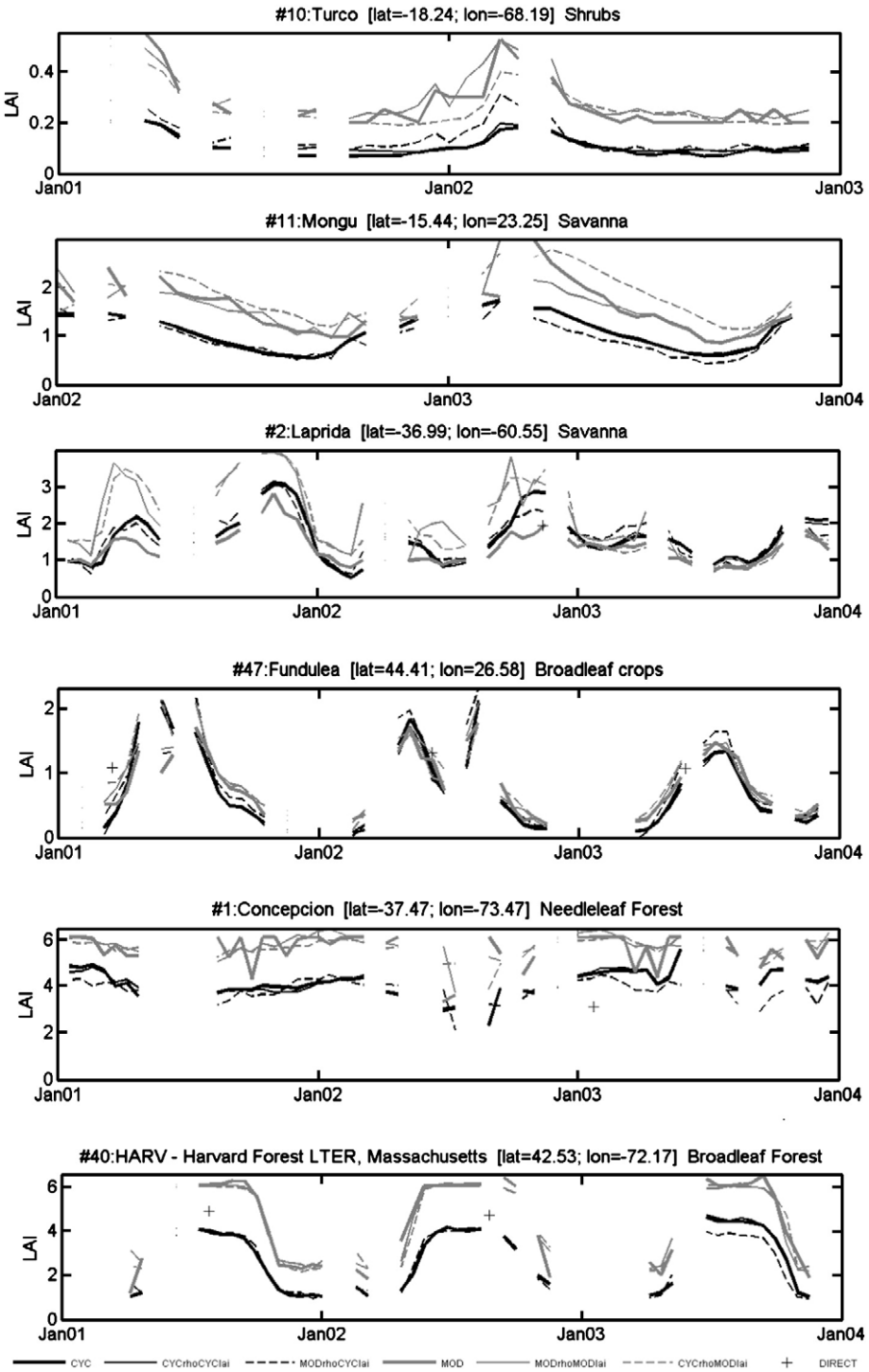

Fig. 2. Temporal evolution of CYCLOPES, MODIS LAI products and NNT estimates for the period 2001–2003 over six 3 km × 3 km BELMANIP sites representing six MODIS biome classes.

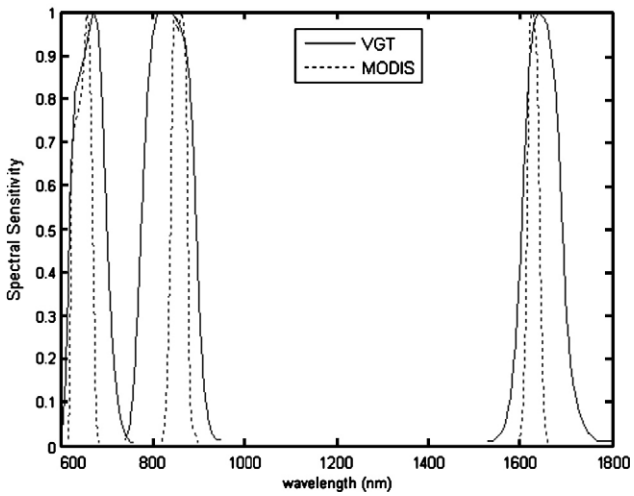

Fig. 3. Spectral response function of VEGETATION and MODIS.

Vegetation user's guide available online at http://vegetation.cnes.fr/system/content.html#userguide; Wolfe et al., 1998). Higher impacts are expected from the radiometric calibration, atmospheric and geometric corrections (Verger et al., 2005).

For the spectral dimension, a comparison between spectral response of both sensors for the three bands considered in this study shows that MODIS bands are "narrower" than those of VEGETATION, but are within the spectral range of variation of the VEGETATION ones (Fig. 3). However, a particular simulation study (not shown here for the sake of brevity) achieved at the top of the atmosphere level and encompassing a large range of vegetation types, atmospheric conditions and geometric configuration, demonstrated that despite these spectral differences, very good agreement without biases were expected between homologous pairs of bands.

Pairs of homologous CYCLOPES and MODIS products were compared over the whole data base described previously. Linear rectangular regression between normalized reflectances of the two products for each of the three bands was preferred to classical linear regression since it provides equal treatment of the two variables. For sake of simplicity, uncertainties were not accounted for in the regression computation because they are not precisely known. In addition, these uncertainties should be of the same order of magnitude for the two variables. In these conditions, slope and offset of the regression computed with or without taking uncertainties into account would be very similar. Results show good agreement between MODIS and CYCLOPES reflectance products (Fig. 4) although CYCLOPES is slightly, but systematically, lower than MODIS reflectances in the three bands. These biases differ from theoretical previously mentioned simulation study mainly because of the combination of radiometric calibration uncertainties and inaccuracies of atmospheric correction although further investigations are required to better identify and quantify the sources of these differences.

The scatter plots for each band (Fig. 4) shows outliers probably due to unscreened clouds, residual atmospheric effects or snow masking errors. As there are differences in compositing window between products, this could result in a differential weighting of such noisy effects on data. These outliers must be eliminated to improve the consistency between products within this data base. For each individual data (date∗site), the sum of squared relative differences in the three bands between both sensors was computed. This criterion was used to reject data showing the largest discrepancies over the three bands. The 5%, 10%, 15% and 20% showing the largest discrepancies were tentatively rejected, and the corresponding regression performances were computed: when more outliers were rejected, the consistency between CYCLOPES and MODIS products obviously improves, resulting in a higher correlation, a lower root

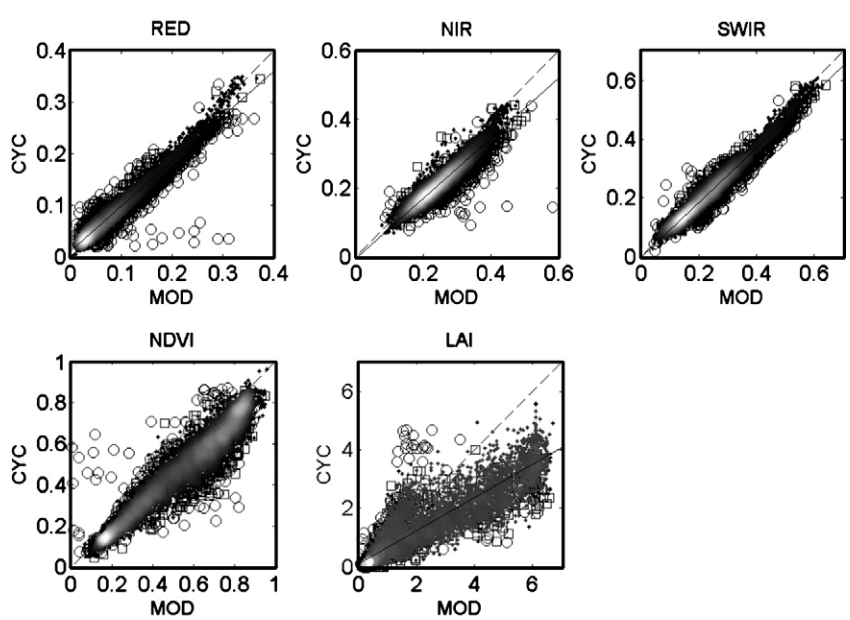

Fig. 4. Density plots between CYCLOPES and MODIS normalized reflectances, NDVI values and LAI products over BELMANIP sites during the 2001–2003 period (n=7572). The 10% (20%) showing the largest reflectance discrepancies in the three bands are indicated with circle (square) symbols.

Table 1
Correlation coefficient (R^2), slope and offset of the rectangular linear regression

Product	Rejection level	n	R^2	RMSE	Slope	Offset
Red reflectance	0%	7572	0.956	0.021 (24%)	0.875±0.003	0.010
	10%	6815	0.985	0.012 (14%)	0.922±0.002	0.008
	20%	6058	0.988	0.010 (13%)	0.935±0.002	0.007
Near infrared reflectance	0%	7572	0.923	0.044 (19%)	0.874±0.004	0.004
	10%	6815	0.950	0.038 (17%)	0.907±0.004	0.009
	20%	6058	0.957	0.035 (16%)	0.926±0.004	0.012
Short wave infrared reflectance	0%	7572	0.977	0.029 (13%)	0.936±0.002	0.003
	10%	6815	0.983	0.025 (11%)	0.952±0.002	0.005
	20%	6058	0.986	0.022 (10%)	0.961±0.002	0.005
LAI	0%	7572	0.897	1.287 (77%)	0.569±0.003	0.088
	10%	6815	0.909	1.295 (75%)	0.574±0.003	0.071
	20%	6058	0.914	1.307 (74%)	0.578±0.003	0.055

The root mean square error (RMSE) corresponds to the square root of the average squared difference between CYCLOPES and MODIS products. Comparison achieved over BELMANIP sites during the 2001–2003 period as a function of the rejection level over reflectances. 0% rejection level corresponds to the original 7572 matches and n refers to the number of samples per rejection level.

mean square error and a slope closer to unity (Table 1). Reflectance consistency improves significantly for the first rejection fractions (5% and 10%) as shown both in Table 1 and Fig. 4, while minor improvements are observed for larger rejection levels (15% and 20%). A similar percentage of data were rejected among the several biome classes for 5% or 10% levels, while more differences between classes were found in the remaining data base when higher rejection levels were applied.

Comparison between CYCLOPES and MODIS LAI products shows a higher scattering as compared to reflectances (Table 1, Fig. 4, Table 3 and graphs on the right of Fig. 5). The systematic lower CYCLOPES LAI values as compared to MODIS ones in dense vegetated areas can be explained partly by the influence of clumping due to differences in product definitions. A closer inspection per biome classes (Fig. 6) shows that good agreement is observed for "grasses and cereal crops" and "broadleaf crops" biome classes. As a matter of fact, they correspond to canopies with very limited leaf clumping that were simulated with essentially 1D model in the MODIS original algorithm. Conversely, differences between the effective CYCLOPES LAI and MODIS 'true' LAI definitions show off for the other biomes, with slopes close to 0.6 on the average between CYCLOPES and MODIS LAI values (Table 3). In addition, some saturation of CYCLOPES LAI is observed for broadleaf forest, for values larger than 4 (Figs. 5 and 6). These results agree also with those of Weiss et al. (2007) who reported an early saturation of CYCLOPES LAI product (values hardly go beyond LAI=4).

Note that most outliers for LAI are eliminated when rejecting data showing inconsistencies between reflectances (Fig. 4). Filtering over LAI values to increase the consistency between CYCLOPES and MODIS LAI products was tentatively applied. However, results (not displayed here) show that improvement on LAI consistency is lower than 3%.

A rejection level of 10% over reflectances was finally selected because it provided a significant improvement of networks performances (see Table 3) while not reducing too much the size of the data base and preserving the statistical distribution of acquisitions per classes.

3. Neural network training process

Because the type of inputs (reflectances in the red, near infrared and short wave infrared and the sun zenith angle) and outputs (LAI) are the same as in the case of the original CYCLOPES LAI algorithm, similar neural networks will be used (Baret et al., 2007). They mainly consist in back-propagation networks made of one layer of five tangent-sigmoid and one layer linear transfer functions, resulting in 26 synaptic

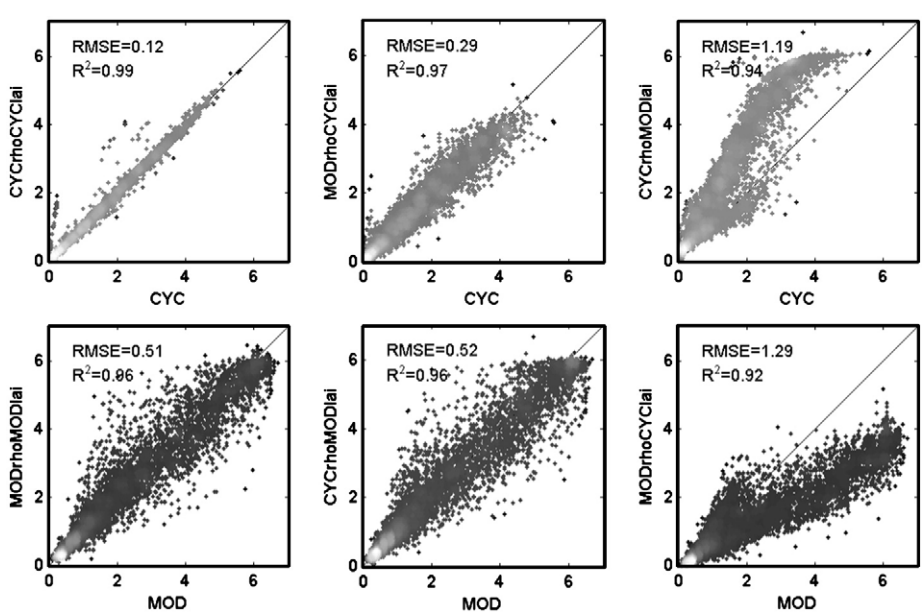

Fig. 5. Comparison between several LAI products over the whole data set (n=6815).

and 6 biases coefficients to be adjusted. The inputs and outputs were scaled by their minimum and maximum values. The Levenberg–Marquardt minimization algorithm was used in the learning process because of its efficient convergence performances (Ngia and Sjoberg, 2000). To prevent hyper-specialization during the training process and test performance of the networks, the data base was split in two parts by randomly selecting cases. Two thirds of the cases were used to train the network (training data base) and the last third to test the hyper-specialization during the training process and perform some validation (test data base). Five networks were trained in parallel, each corresponding to independent random drawing of initial values of synaptic weights and bias. The one providing the best performances over the test data base was selected.

In the original CYCLOPES approach, radiative transfer models were run to simulate actual VEGETATION observations from prior distribution of canopy characteristics. In the proposed approach, actual reflectances observed by VEGETATION (CYCLOPES) or MODIS are associated to the corresponding CYCLOPES or MODIS LAI products in the learning process. Four combinations of reflectances and LAI are therefore

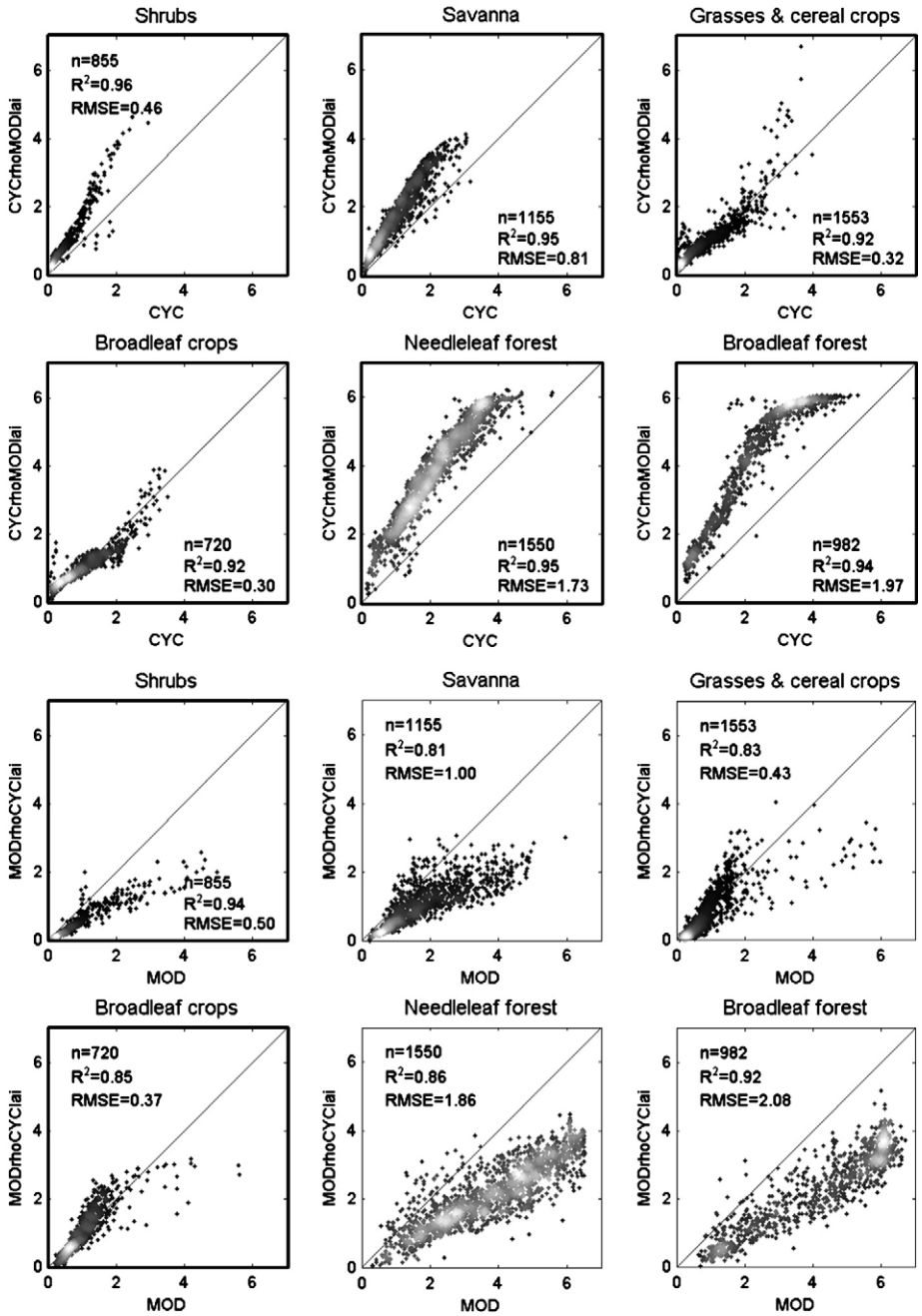

Fig. 6. The six top figures correspond to the comparison between CYCLOPES original products (CYC) and MODIS LAI estimated from CYCLOPES reflectances (CYCrhoMODlai) for each of the 6 biomes. The six bottom figures correspond to the comparison between MODIS original products (MOD) and CYCLOPES LAI estimated from MODIS reflectances (MODrhoCYClai) for each of the 6 biomes.

investigated (Table 2): CYCLOPES observed reflectance with CYCLOPES LAI products (CYCrhoCYClai) or MODIS LAI products (CYCrhoMODlai), or MODIS observed reflectances with CYCLOPES LAI product (MODrhoCYClai) or MODIS LAI products (MODrhoMODlai). These four combinations yield specific results on the capacity of neural networks to mimic a particular algorithm (case of MODrhoMODlai), or to cross-learn a given LAI product from reflectance observations coming from another sensor (cases of CYCrhoMODlai or MODrhoCYClai). The case of CYCrhoCYClai yields obviously only limited information since the CYCLOPES algorithm was already based on a neural network. However, the distribution of vegetation types and observational conditions and uncertainties in this training data base may be different from the characteristics used in the training data base of the original CYCLOPES products. In addition, original CYCLOPES products were not biome dependant, while in the present approach specific learning is applied to each of the six classes as in the case of the MODIS original algorithm. The same definition of the 6 biome types as in the original MODIS products is therefore kept along this study. The approach consisting in training a dedicated neural network for each class is compared to the one based on learning a single neural network across all the classes.

Results show that training networks per classes always improves significantly (probability higher than 0.9999) LAI estimates as compared to training across classes (Table 2). However for CYCLOPES LAI products (CYCrhoCYClai and MODrhoCYClai), improvement in performances is only marginal because the original CYCLOPES LAI products were not dependant on classes. The slight improvement observed may be due to a more specific training achieved over more homogeneous learning data base. Conversely, improvement is much larger for MODIS LAI products (CYCrhoMODlai and MODrhoMODlai) for which the original algorithm was biome dependent. However, the distribution of residuals between training per class and across classes (Fig. 7) shows that the effect is small, with most of residuals within $\pm 0.5\ m^2\ m^{-2}$. Note also that the input reflectance data set (CYCLOPES or MODIS) has a second order influence on the performances, confirming the good consistency observed previously (Fig. 4).

4. Evaluation of NNT performances

NNT performances are evaluated for the four combinations of reflectances and LAI. Indirect validation is first achieved, consisting in analyzing the self-consistency of products as well as the consistency between the several products and the original CYCLOPES and MODIS LAI products. Then, comparison with ground measurements (direct validation) is presented.

Table 2
The four combinations of products investigated along with the RMSE values evaluated over the test data set

	CYCLOPES reflectances	MODIS reflectances
CYCLOPES LAI	CYCrhoCYClai 0.119 (0.129)	MODrhoCYClai 0.297 (0.305)
MODIS LAI	CYCrhoMODlai 0.525 (0.609)	MODrhoMODlai 0.502 (0.558)

Numbers in parenthesis correspond to RMSE values when the learning is achieved across all classes.

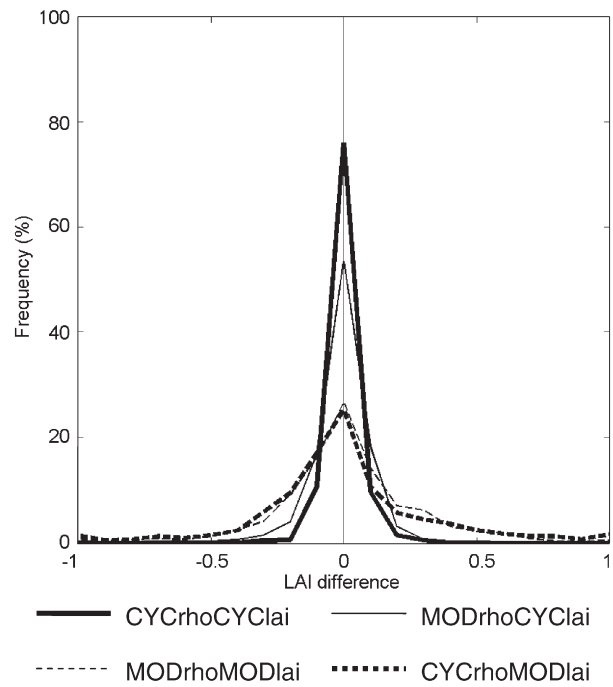

Fig. 7. Histogram of differences in LAI estimates when networks are trained per classes or across classes. Results computed over the test data base for CYCLOPES (CYC) and MODIS (MOD) reflectances (rho) and LAI products.

4.1. Consistency assessment

The temporal consistency of NNT LAI estimates as compared to MODIS and CYCLOPES products is first investigated. Then, statistical distributions of the several biome classes are compared. Indirect validation is achieved over the BELMANIP sites during the 2001–2003 period for the 7572 CYCLOPES and MODIS best reflectance matches selected in Section 2.3.

4.1.1. Temporal consistency

Temporal consistency was evaluated by the smoothness level of the temporal profiles. As a matter of fact, except in extreme situations such as fire, flooding, or change of land use, LAI results from incremental processes such as photosynthesis, assimilate allocation or senescence, producing relatively slow thus smooth variation with time. This was evaluated as proposed by Weiss et al. (2007) using the difference δ between LAI(t) product value at date t and the mean value between the two bracketing dates: $\delta = 1/2(\mathrm{LAI}(t+\Delta t)+\mathrm{LAI}(t-\Delta t)) - \mathrm{LAI}(t)$, where Δt is the temporal sampling interval. Difference δ is computed only if the two bracketing LAI values at $(t-\Delta t)$ and $(t+\Delta t)$ exist. The smoother the temporal evolution, the smaller the δ difference should be. Histograms of δ (Fig. 8) show that MODIS original products (MOD) are the most 'shaky', while temporal profiles of other products are smoother particularly when CYCLOPES reflectances are used. Obviously, these results could partly be explained

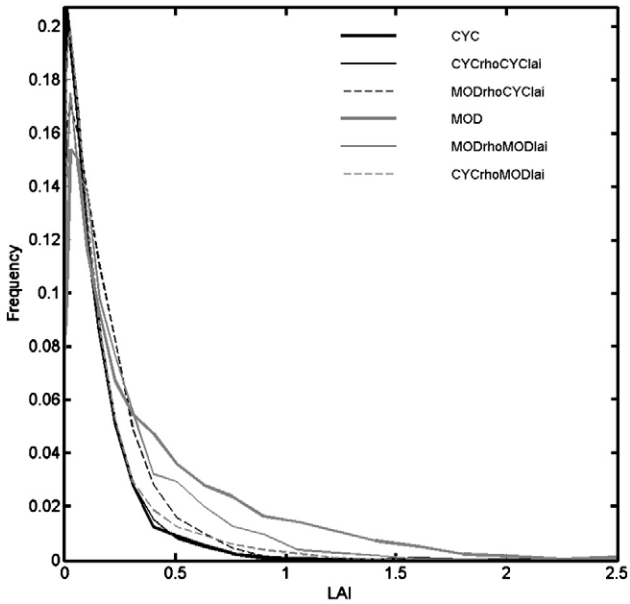

Fig. 8. Histogram of the δ value for the 4 combinations of products developed and the original CYCLOPES (CYC) and MODIS (MOD) products.

by the actual length of the compositing window and associated temporal resolution of the products as already pointed out in section 2.3: MODIS original LAI products are 8 days composite, as compared to 24 days for MODrhoMODlai and 30 days for CYCLOPES (CYC) original products and 40–60 days for MODrhoCYClai, CYCrhoCYClai and CYCrhoMODlai products. The smoothness also depends on the number of "valid" observations used (and how "valid" are the observations). Indeed, NNT products mainly depend on the smoothness of input reflectance values since NNT output is a continuous function of inputs. Although the same number of CYCLOPES and MODIS observations was considered in the data base by eliminating observations when data were missing for at least one of the products, this number will be variable both for MODIS 16 days and CYCLOPES reflectance products. Nevertheless, because of similarities in the compositing algorithms used for MODIS and CYCLOPES reflectance products, the number of observations used should be on the average proportional to the length of the compositing window.

To better document the temporal behaviour of each LAI product, time courses over a selection of sites corresponding to a range of vegetation types will be described: Turco (Bolivia) classified as "shrubs"; Mongu a "savanna" site located in western Zambia; Laprida (Argentina) classified as "savanna" by MODIS land cover but corresponding actually to grassland; Fundulea (Romania) cereal and broadleaf site classified as "grassland and cereal crop"; Concepcion (Chile) corresponding to a mixed forest classified as "needleleaf forest" by MODIS land cover; and Harvard (Massachusetts, USA) mixed forest classified as "broadleaf forest" by MODIS. For more details about these sites, see Table 4.

A good agreement on the seasonality and its phasing is observed between the original CYCLOPES and MODIS products and the four combinations of NNT LAI estimates (Fig. 2). However, LAI magnitude shows large discrepancies, except for Fundulea agricultural site. Estimates from networks trained over CYCLOPES LAI data (CYCrhoCYClai and MODrhoCYClai) are very similar to CYCLOPES original products. Conversely, LAI estimated from networks trained with MODIS LAI products (MODrhoMODlai and CYCrhoMODlai) is closer to the original MODIS products. The best agreement was obviously found between the original CYCLOPES (respectively MODIS) LAI products and NNT estimates based on CYCLOPES (respectively MODIS) LAI and normalized reflectances.

LAI estimated from MODIS reflectance (MODrhoMODlai and MODrhoCYClai) presents a shakier time course than LAI

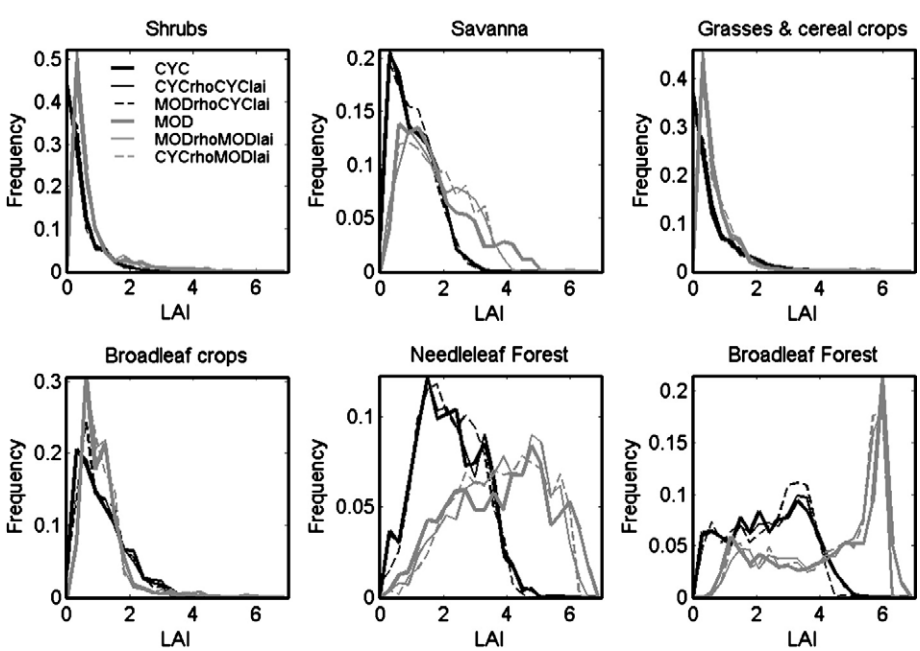

Fig. 9. Distributions of CYCLOPES, MODIS LAI products and NNT estimates for six MODIS biome classes. The number of samples per biome is listed in Table 3.

Table 3
Statistics of a per classes comparison between CYCLOPES, MODIS LAI products and NNT estimates over BELMANIP filtered data base during the period 2001–2003 for each of the six biome types: root mean square error (RMSE), correlation coefficient (R^2), slope and offset of the rectangular linear regression (y=slope x+offset with x corresponds to the lines in the table and y to the columns)

	RMSE / R^2	CYC	CYCrhoCYClai	MODrhoCYClai	MOD	MODrhoMODlai	CYCrhoMODlai
Shrubs (n=844)	CYC		**0.04**	0.10	0.50	0.47	0.46
	CYCrhoCYClai	**1.00**		**0.11**	0.52	0.49	0.47
	MODrhoCYClai	0.97	**0.97**		**0.50**	0.46	0.48
	MOD	0.93	0.93	**0.94**		**0.20**	0.19
	MODrhoMODlai	0.94	0.93	0.97	**0.96**		**0.19**
	CYCrhoMODlai	0.96	0.96	0.95	0.97	**0.96**	
Savanna (n=1145)	CYC		**0.05**	0.20	0.99	0.85	0.81
	CYCrhoCYClai	**1.00**		**0.19**	1.00	0.85	0.81
	MODrhoCYClai	0.95	**0.96**		**1.00**	0.83	0.84
	MOD	0.81	0.80	**0.81**		**0.54**	0.57
	MODrhoMODlai	0.88	0.88	0.92	**0.87**		**0.35**
	CYCrhoMODlai	0.94	0.94	0.91	0.85	**0.93**	
Grasses and cereal crops (n=1539)	CYC		**0.13**	0.21	0.43	0.32	0.32
	CYCrhoCYClai	**0.98**		**0.20**	0.42	0.30	0.30
	MODrhoCYClai	0.95	**0.95**		**0.44**	0.27	0.37
	MOD	0.84	0.85	**0.83**		**0.33**	0.31
	MODrhoMODlai	0.91	0.92	0.94	**0.89**		**0.26**
	CYCrhoMODlai	0.92	0.93	0.88	0.91	**0.92**	
Broadleaf crops (n=717)	CYC		**0.16**	0.29	0.40	0.41	0.30
	CYCrhoCYClai	**0.98**		**0.25**	0.39	0.38	0.27
	MODrhoCYClai	0.92	**0.94**		**0.37**	0.29	0.32
	MOD	0.84	0.84	**0.85**		**0.29**	0.30
	MODrhoMODlai	0.83	0.84	0.90	**0.90**		**0.30**
	CYCrhoMODlai	0.92	0.93	0.87	0.89	**0.88**	
Needleleaf forest (n=1548)	CYC		**0.10**	0.40	1.87	1.78	1.73
	CYCrhoCYClai	**1.00**		**0.39**	1.87	1.78	1.73
	MODrhoCYClai	0.92	**0.92**		**1.86**	1.73	1.77
	MOD	0.83	0.84	**0.86**		**0.72**	0.76
	MODrhoMODlai	0.89	0.89	0.97	**0.88**		**0.53**
	CYCrhoMODlai	0.95	0.95	0.91	0.87	**0.92**	
Broadleaf forest (n=971)	CYC		**0.19**	0.40	2.09	2.00	1.97
	CYCrhoCYClai	**0.99**		**0.37**	2.05	1.97	1.93
	MODrhoCYClai	0.95	**0.95**		**2.08**	1.98	1.98
	MOD	0.89	0.89	**0.92**		**0.61**	0.61
	MODrhoMODlai	0.92	0.93	0.97	**0.94**		**0.39**
	CYCrhoMODlai	0.94	0.95	0.95	0.94	**0.97**	

In parenthesis the probability of slope being different from 1. Numbers in bold highlight the main features discussed in the text.

estimated using CYCLOPES reflectances (CYCrhoCYClai and CYCrhoMODlai), confirming the previous results about the smoothness as a function of the size of the compositing window (Fig. 8).

Note that for Laprida site, significant differences between the original MODIS LAI and CYCrhoMODlai and MODrhoMODlai estimates were found. This feature may be due to MODIS LAI biome dependence and land cover misclassification of Laprida site as it was classified as "savanna" in 2001 and 2002, and as a "broadleaf crop" in 2003 while being a grassland site after VALERI ground information: it should therefore be classified as "grasses and cereal crops". Misclassification impacts affect more the performance of NNT estimates as compared to the MODIS original product that seems to be more temporally consistent from 2001 to 2003 in Laprida site (Fig. 2). This can be an influence of the limited size of the data base used for training NNT. The effect of land cover misclassification for NNT estimates varies depending on the similarities between biomes. Since "broadleaf crops" distributions of NNT estimates as compared to MODIS and CYCLOPES LAI products are similar to "grasses and cereal crops" LAI distributions (Fig. 6), a good agreement between NNT estimates and original products was found in 2003 while higher discrepancies are found in the 2001–2002 period due to the greater differences between "savanna" and "grasses and cereal crops" distributions (Fig. 6).

4.1.2. Statistical distributions per biome type

Histograms of LAI values (Fig. 9) show consistent distributions across all biomes between products derived from the same original LAI products: CYC, CYCrhoCYClai and MODrhoCYClai for CYCLOPES original LAI products, and MOD, MODrhoMODlai and CYCrhoMODlai for the original MODIS LAI products. While some similarities are observed

Offset / Slope	CYC	CYCrhoCYClai	MODrhoCYClai	MOD	MODrhoMODlai	CYCrhoMODlai
CYC		**0.01**	0.01	0.03	0.05	0.06
CYCrhoCYClai	**1.03(1)**		**0.00**	0.01	0.04	0.05
MODrhoCYClai	1.03(0.99)	**1.00(0.59)**		**0.01**	0.04	0.04
MOD	0.56(1)	0.54(1)	**0.54(1)**		**0.02**	0.03
MODrhoMODlai	0.58(1)	0.56(1)	0.58(1)	**1.04(1)**		**0.01**
CYCrhoMODlai	0.59(1)	0.57(1)	0.57(1)	1.05(1)	**1.00(0.65)**	
CYC		**0.00**	0.05	−0.13	0.18	0.25
CYCrhoCYClai	**1.00(0.92)**		**0.05**	−0.14	0.17	0.25
MODrhoCYClai	1.05(1)	**1.05(1)**		**−0.24**	0.12	0.15
MOD	0.55(1)	0.54(1)	**0.52(1)**		**0.22**	0.27
MODrhoMODlai	0.66(1)	0.66(1)	0.64(1)	1.16(1)		**0.04**
CYCrhoMODlai	0.69(1)	0.69(1)	0.65(1)	1.19(1)	**1.02(0.99)**	
CYC		**0.01**	0.03	0.12	0.20	0.18
CYCrhoCYClai	**1.04(1)**		**0.02**	0.10	0.18	0.16
MODrhoCYClai	1.06(1)	**1.02(0.99)**		**0.08**	0.17	0.15
MOD	0.93(1)	0.90(1)	**0.88(1)**		**0.10**	0.07
MODrhoMODlai	1.08(1)	1.04(0.99)	1.02(0.99)	**1.15(1)**		**−0.03**
CYCrhoMODlai	1.03(0.99)	0.99(0.83)	0.97(0.99)	1.10(1)	**0.95(1)**	
CYC		**0.03**	0.11	0.14	0.19	0.23
CYCrhoCYClai	**1.03(1)**		**0.08**	0.11	0.16	0.20
MODrhoCYClai	1.12(1)	**1.08(1)**		**0.02**	0.07	0.14
MOD	1.13(1)	1.09(1)	**1.00(0.65)**		**0.06**	0.12
MODrhoMODlai	1.25(1)	1.20(1)	1.10(1)	**1.09(1)**		**0.06**
CYCrhoMODlai	1.27(1)	1.22(1)	1.14(1)	1.13(1)	**1.04(0.99)**	
CYC		**0.01**	0.20	0.16	0.73	0.83
CYCrhoCYClai	**1.01(0.99)**		**0.18**	0.14	0.71	0.81
MODrhoCYClai	1.10(1)	**1.09(1)**		**−0.16**	0.53	0.49
MOD	0.60(1)	0.59(1)	**0.55(1)**		**0.51**	0.55
MODrhoMODlai	0.70(1)	0.70(1)	0.66(1)	**1.15(1)**		**0.04**
CYCrhoMODlai	0.72(1)	0.72(1)	0.65(1)	1.16(1)	**1.01(0.91)**	
CYC		**0.04**	0.15	0.63	0.99	0.92
CYCrhoCYClai	**1.00(0.78)**		**0.11**	0.59	0.95	0.88
MODrhoCYClai	1.07(1)	1.07(1)		**0.44**	0.84	0.72
MOD	0.66(1)	0.66(1)	**0.62(1)**		**0.36**	0.25
MODrhoMODlai	0.73(1)	0.73(1)	0.69(1)	**1.09(1)**		**−0.12**
CYCrhoMODlai	0.72(1)	0.72(1)	0.67(1)	1.07(1)	**0.98(0.99)**	

between these two families of LAI products for "shrubs", "savanna", "grasses and cereal crops", and "broadleaf crops", larger discrepancies show off for forest canopies in agreement with previous validation studies (Weiss et al., 2007). An early saturation of LAI products derived from CYCLOPES (CYC, CYCrhoCYClai and MODrhoCYClai) appears, with maximum LAI values near 5. Products derived from MODIS LAI show a broader distribution of values for forests with a narrow peak around 6 for "broadleaf forests".

4.1.3. Scatter plots between the several products

Comparison between the four combinations of LAI products and the two original (spatially and temporally resampled) LAI and CYCLOPES LAI products was achieved at the 16 days temporal frequency. Associated statistics including root mean square error (RMSE computed with the 1:1 line as a reference), correlation coefficient, slope and offset are presented in Table 3. Note that the rectangular linear regression was selected for the same reasons as previously for reflectance products comparison, and for the same reasons, uncertainties in the two LAI products to be compared were not accounted for since they were not known, but should be of the same order of magnitude. Statistics were computed for each of the 6 biome types.

The capacity of neural networks to replace efficiently existing algorithms is here demonstrated. Although this was obviously not too difficult for CYCLOPES LAI products that were already derived from a neural network approach, the NNT were able to match the CYCLOPES LAI with absolute errors ranging from 0.12 with CYCLOPES reflectances (see top left graph of Fig. 5) to 0.3 with MODIS reflectances (top centre of Fig. 5) representing levels well under the 0.7 absolute error of the CYCLOPES LAI products compared to in situ data (see Section 4.2). That was more questionable for the MODIS LAI

algorithm which was based on other principles, but the NNT proved performing well with an overall absolute error of 0.5 both with MODIS (bottom left of Fig. 5) and CYCLOPES (bottom centre of Fig. 5) reflectances. In addition to the intrinsic limitations of the NNT approach, the degradation of estimation performances was mainly due to difficulties in training the neural networks because of the limited size of the learning data base and the loss of causality in the relationship between LAI and reflectance due to the noise associated to measurements and algorithms, inaccurate ancillary information (land cover) or imperfect theory in the algorithms. Degradation of performances for MODIS as compared to CYCLOPES LAI products might be due to the larger instability observed within the original MODIS LAI products, partly due to the smaller compositing period, but also probably partly due to the size of the LUT and the way the solution is selected in the original MODIS algorithm. Further, errors in biome class assignment may also explain part of the degradation of performances.

The capacity of neural networks to estimate LAI products from reflectances coming from another sensor is also demonstrated (Table 3 and centre graphs in Fig. 5): very good agreement is observed when comparing the original CYCLOPES LAI product, with LAI estimates from MODIS reflectances; reciprocally, good agreement is observed between the original MODIS products and NNT estimates from CYCLOPES reflectances. No biases are observed over the whole range of variation as observed in Fig. 5 and attested in Table 3 by the slopes (close to 1.0) and the offsets (close to 0.0), except for NNT estimates of MODIS LAI from both MODIS or CYCLOPES reflectances over "savanna", "broadleaf crops" and "needleleaf forests". Note that NNT estimates of MODIS LAI from MODIS reflectances are very consistent with NNT estimates of MODIS LAI from CYCLOPES reflectances.

However, NNTs could not obviously reconcile discrepancies between the original CYCLOPES and MODIS LAI products as observed by Weiss et al. (2007), Table 3 and Fig. 4.

4.2. Direct validation

Original MODIS and CYCLOPES LAI products and the four NNT estimates were compared with direct ground measurements of effective and true LAI (Fig. 10). These measurements result from several international field campaigns and are available for about 40 sites widely distributed both in location and land cover type. The methods used to scale up local ground measurements to the site level are described in Morisette et al. (2006). Note that ground measurements could be derived from several devices and interpretation techniques, and may provide estimates of effective LAI values (assuming the canopy as a turbid medium) or true LAI values when leaf clumping is accounted for (Chen et al., 2006). In this study, 18 sites (Table 4) were matching our CYCLOPES and MODIS observations, some of the sites being sampled several times.

Results (Fig. 10) show that LAI derived from the original LAI CYCLOPES products perform the best both for the effective and true LAI values, scoring the lowest RMSE values. Slight differences are observed depending on the source of input reflectance used (differences in the overall RMSE of 5% in CYCLOPES LAI and 10% in MODIS LAI relative to ground measurements). LAI estimates derived from the original MODIS LAI products show larger RMSE values both for effective LAI

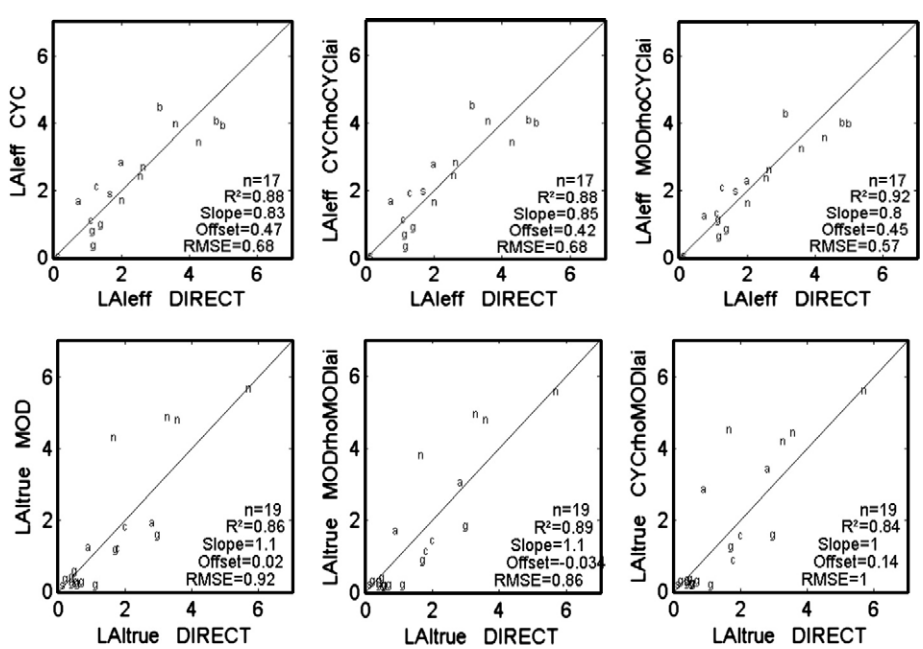

Fig. 10. Comparison of CYCLOPES, MODIS LAI products and NNT estimates with direct ground measurements of effective LAI (17 points) and true LAI (19 points). Letter markers correspond to different biome classes: shrubs (s), savanna (a), grasses and cereal crops (g), broadleaf crops (b), needleleaf forest (n) and broadleaf forest (b). Slope and offset values were calculated with the ordinary least square linear regression.

Table 4
Sites used for the direct validation

Site name	Meas. date	Biome class	Lat. (°)	Long. (°)	LAIeff	LAItrue	Source
Concepcion	23/01/2003	Broadleaf forest	−37.47	−73.47	3.0		Valeri
Laprida	13/11/2002	Savanna	−36.99	−60.55	1.9	2.7	Valeri
Turco	29/08/2002	Shrubs	−18.24	−68.19	0.0	0.0	Valeri
Haouz	25/03/2003	Shrubs	31.66	−7.60	1.6		Valeri
Sevilleta	26/07/2002	Grasses and cereal crops	34.35	−106.69		0.1	BigFoot
	22/08/2002	Grasses and cereal crops				0.3	BigFoot
	09/09/2002	Grasses and cereal crops				0.4	BigFoot
	15/11/2002	Grasses and cereal crops				0.3	BigFoot
	23/06/2003	Grasses and cereal crops				0.6	BigFoot
	28/07/2003	Grasses and cereal crops				0.5	BigFoot
	15/09/2003	Grasses and cereal crops				0.5	BigFoot
	21/11/2003	Grasses and cereal crops				1.0	BigFoot
Konza prairie	16/08/2001	Grasses and cereal crops	39.09	−96.57		2.9	BigFoot
Harvard forest	26/07/2001	Broadleaf Forest	42.53	−72.17	4.9		BigFoot
	24/08/2002	Broadleaf Forest			4.7		BigFoot
Sud_Ouest	20/07/2002	Broadleaf crops	43.51	1.24	1.2	1.9	Valeri
Alpilles	20/07/2002	Broadleaf crops	43.81	4.74	1.0	1.7	Valeri
Larzac	12/07/2002	Savanna	43.94	3.12	0.6	0.8	Valeri
Metl Oregon	24/09/2002	Needleleaf Forest	44.45	−121.57	1.9		BigFoot
Fundulea	17/03/2001	Grasses and cereal crops	44.41	26.59	1.1		Valeri
	09/06/2002	Grasses and cereal crops			1.3	1.6	Valeri
	31/05/2003	Grasses and cereal crops			1.1		Valeri
Larose	19/08/2003	Needleleaf Forest	45.38	−75.22	3.5	5.6	Valeri
Thompson	15/07/2001	Needleleaf Forest	56.05	−98.16		1.6	BigFoot
NOBS-BOREAS	14/07/2001	Needleleaf Forest	55.89	−98.48		3.5	BigFoot
	14/07/2002	Needleleaf Forest				3.2	BigFoot
Jarvselja	27/06/2003	Needleleaf Forest	58.30	27.26	4.2		Valeri
Hirsikangas	02/08/2003	Needleleaf Forest	62.64	27.01	2.5		Valeri
Flakaliden	20/08/2002	Needleleaf Forest	64.11	19.47	2.5		Valeri

Data sources are mainly BigFoot (Cohen et al., 2006a,b) and Valeri (http://www.avignon.inra.fr/valeri).

as expected, but also for true LAI. Part of this feature could be explained by the instability in the algorithm, but also some overestimation is observed for "needleleaf forests" and in a lesser degree for "savanna" while LAI for the other biomes show some underestimation.

Because of the low number of data points, it is difficult to draw firm conclusions. As a matter of fact, there are not enough sites available for the larger LAI values, where maximum differences between CYCLOPES and MODIS show off. Additionally, ground measurements are associated to errors and biases that are difficult to estimate. Assuming that these ground measurements uncertainties are normally distributed with relative error of 15% (Verger et al., submitted for publication), and that products are associate to an intrinsic 0.5 (absolute) error as expected by users, then, a simple Monte Carlo simulation applied over the 18 available effective LAI ground measurements shows that direct validation statistics would be RMSE = 0.59 ± 0.10, R^2 = 0.93 ± 0.03, slope = 0.97 ± 0.12 and offset = 0.05 ± 0.19. These figures are not too far from our best performances for LAI products.

5. Conclusion

This study demonstrates the versatility and performances of neural networks to learn several LAI products from several input reflectance products. NNT trained with the same LAI products and different input reflectance products showed very consistent results. This was also a consequence of the very good consistency observed between reflectance products of the two sensors considered: VEGETATION (CYCLOPES) and MODIS. Note that the approach does not need a very accurate absolute calibration of reflectance products: the main requirement here is a very high degree of spatial and temporal consistency of reflectances in each band.

Comparison between MODIS original products and NNT estimates either derived from MODIS or CYCLOPES reflectances show that MODIS algorithm has some instability that results in more shaky temporal profiles. Part of these instabilities may be attributed to the shorter temporal resolution (8 days) of the original MODIS LAI products. However, there might be some intrinsic effects associated to the size of the LUTs, the way the solutions are selected, or errors in biome classification. NNT training seems to smooth out efficiently part of the instabilities in MODIS original products. The compositing period likely resulted in lower temporal variability in CYCLOPES versus MODIS reflectances and derived NNT LAI estimates since only 61% of the signal collected in CYCLOPES compositing time window is contained in the 16 days MODIS compositing window for reflectance.

The main differences between LAI products considered in this study are driven by differences between the original MODIS and CYCLOPES LAI products. Although CYCLOPES includes some clumping at the landscape level, its definition is closer to an effective LAI obtained with a turbid medium canopy assumption. Conversely, MODIS includes some clumping at the plant level that makes its product closer to

the definition of the true LAI. Note that for CYCLOPES LAI products, training without distinction between classes does not provide significant improvement as compared to training for each individual biome class. Conversely, significant differences show off for MODIS for which the original LAI products were tuned for each biome class independently. For "grasses and cereal crops" and "broadleaf crops", because leaf clumping is actually very limited, MODIS and CYCLOPES LAI products agree very well. For the other biomes, and particularly forests, both products still show relatively good consistency, with however a systematic bias corresponding probably to leaf clumping.

Direct validation showed that NNT estimates using CYCLOPES LAI products perform the best when compared to effective LAI measurements. Performances are close to the targeted ones when including uncertainties in ground measurements (assumed to be around 15% relative) for LAI product. This would indicate that with small improvements in both ground measurements and retrieval algorithms, target product performances requirements would be soon reached at least for the effective LAI. True LAI is much more complex, and presumably need additional information on leaf clumping which is probably not accessible using only the spectral dimension of remote sensing observations.

Because of constraints coming from the original products considered, results have been obtained at a degraded spatial resolution of 3 km × 3 km. Similarly, the temporal resolution was quite broad, from 16 to 40–60 days. However, the principles developed in this study should also apply to better spatial and temporal resolution products, providing that output LAI products are consistently linked to input reflectance in the training data base. It could be also applied to any other products providing that a strong link exists with the input remote sensing signals. The quality of the training data base, mainly driven by the number, distribution and consistency of the inputs (radiometric signals) and outputs (the products) is critical for the success of the approach. In this study, the data base was relatively limited although large enough for a good training. However, it was not possible to get fully independent training and evaluation processes except in the case of the direct validation exercise. This aspect should certainly be improved when going from demonstration (this study) to more operational applications.

This study opens avenues for the development of consistent multi-sensor operational products. Training networks over the same LAI data base with input reflectances coming from several sensors would allow easily fusing the products for improved continuity and performances. This would provide a possible way to build 'virtual constellations' from different sensors, and exploit them in synergy. This issue will be addressed in depth in a forthcoming study.

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